A Switching Weighted Adaptive Median Filter for Impulse Noise Removal

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ABSTRACT
Images are often corrupted by impulse noise due to a noisy sensor or channel transmission errors. The goal of impulse noise removal is to suppress the noise by preserving the integrity of edges and detail information. In this paper, a new filter called Switching Weighted Adaptive Median (SWAM) filter is proposed for effective suppression of impulse noise which is used to incorporate the Recursive Weighted Median (RWM) filter and the Switching Adaptive Median (SAM) filter. The adaptive window size is selected using RWM and the output image produced by this filter with least mean square error is considered as input image to SAM filter where impulse detection mechanism is adopted. In this mechanism, the noise is attenuated by estimating the values of noisy pixels with a switch based median filter applied exclusively to those neighborhood pixels not labeled as noisy. Simulation results show consistent and stable performance across a wide range of noise density ranging from 10% to 90%. Unlike the filters like SMF, AMF, WMF and RWM, in the proposed SWAM filter, the window size is selected first based on the presence of the noise density which helps to preserve 2D edge structures of image and delivers a better performance with less computational complexity even at high density impulse noise.

Keywords
Impulse noise, Switching Adaptive Median filter, Recursive Weighted Median filter, Impulse detection

1. INTRODUCTION
The least square method based algorithms have been used successfully to preserve the edges and details for images which are corrupted by Gaussian noise. These methods fail in the presence of impulse noise because the noise is heavily tailed. Moreover, restoration will alter all pixels in the image including those noisefree pixels [3]. The objective of impulse noise removal is to suppress the noise by preserving the integrity of edges and detail information for which the non linear digital filters are used. The effective removal of impulse noise often leads to images with blurred and distorted features. Hence the filtering should be applied only to corrupted pixels while leaving uncorrupted pixels intact [16, 4, 12]. The Standard Median Filter (SMF) was once the most popular non linear digital filter for removing impulse noise because of its good denoising power and computational efficiency [2, 6]. But the main draw back of this filter is that it is effective only for low noise densities. At high noise densities, SMFs often exhibit blurring for large window size and insufficient noise suppression for small window size [13, 11].

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. The adaptive median filter, multistage median filter or the median filter based on homogeneity information are called decision based or 'switching' filters [15, 10]. 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. It has been proved that Recursive Weighted Median (RWM) filter produces better results when compared to other median type filters [1]. When the noise level is over 50% some details and edges of the original image are smeared by the filter. Different remedies have been proposed [5, 9, 7]. Lin and Huang proposed adaptive algorithms for filtering impulse noise [5]. These algorithms are complex and the results are not better, because the window size is selected based on the threshold values. These disadvantages can be overcome by using RWM filter where a high degree of noise suppression and preservation of image sharpness can be achieved. RWM 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 or reference 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 filter. Due to this the unwanted filtering of uncorrupted pixels and blurring are reduced even at high density noise.

2. SWITCHING WEIGHTED ADAPTIVE MEDIAN FILTER

In this paper, a novel Switching Weighted Adaptive Median Filter (SWAM) is proposed that employs the switching scheme with two stages based on impulse detection mechanism. The objective of the proposed filter is to utilize the RWM filter and SAM filter to define more general operators [14, 8]. In the first stage, the size of the adaptive window is selected by RWM and the output image produced by this filter is considered as the input image for the second stage where impulse noise detection mechanism is implemented.

We assume that the image is of size $M \times N$ having 8-bit gray scale pixel resolution of $I \in [0, 2$. Now a large Window $W^x_{i,j}$ is taken whose central pixel is $x(i, j)$. In the conventional switching median filter, the output of the filter is given by

$$y(i, j) = \begin{cases} m^x_{i,j}; if \ |m^x_{i,j} - x(i, j)| > threshold \\ x(i, j); otherwise \end{cases} \quad (1)$$

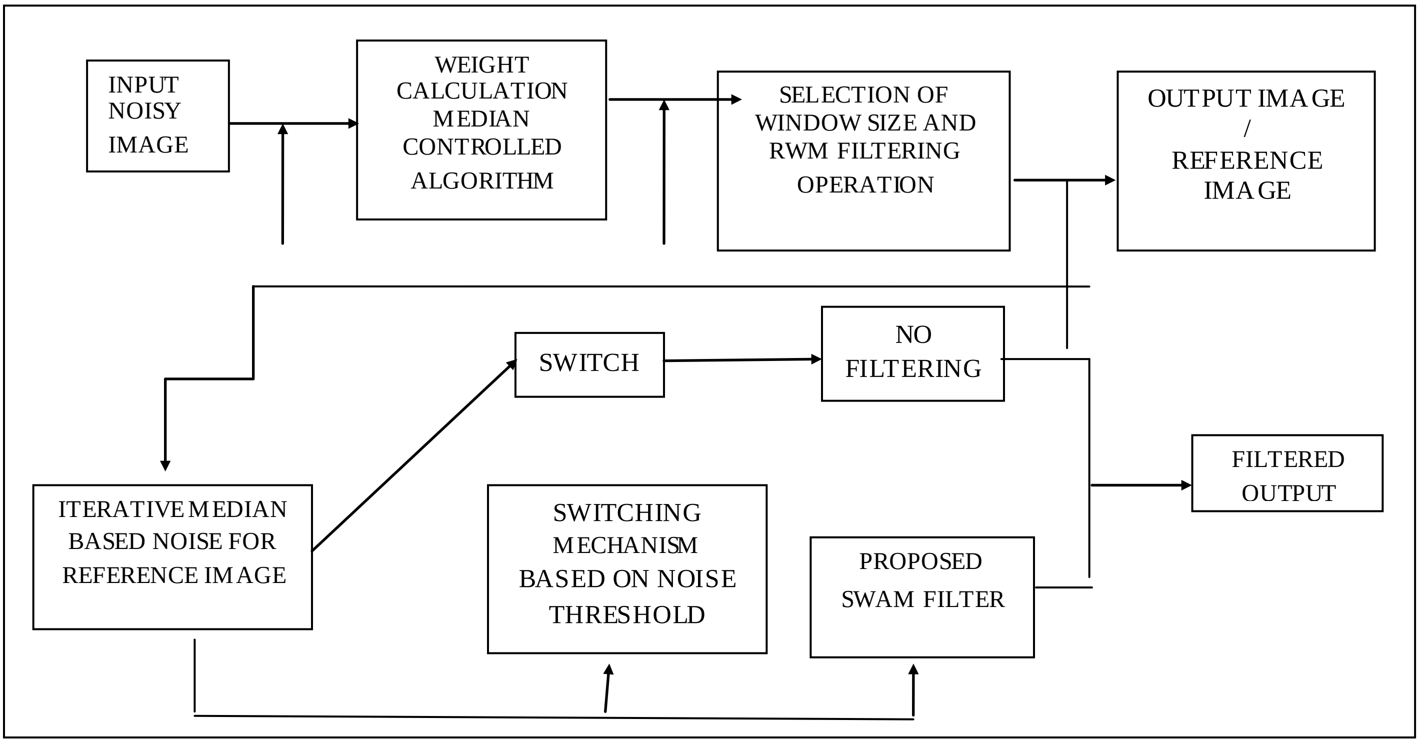


Fig 1: Diagram for proposed Switching Weighted Adaptive Median (SWAM) filter

3. IMPULSE NOISE MODEL

The impulse detection is based on the assumption that a noise pixel in the filtering window takes a gray value which is substantially different from the neighbouring pixels, whereas noise-free regions in the image have locally smooth varying gray levels separated by edges. In the switching median filter, 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. where, $m^x_{i,j}$ represents the median value of the pixels inside the filtering window. When the above scheme is applied for impulse detection, a binary flag image $\{f(i, j)\}$ is constructed such that $f(i, j) = 1$ if the pixel $x(i, j)$ is noisy and $f(i, j) = 0$ if the pixel $x(i, j)$ is noiseless. Now during filtering operation, the noisy pixels are replaced by the median of the noise-free pixels [17].

4. STRUCTURE OF RECURSIVE WEIGHTED MEDIAN FILTER

The RWM filter detects and removes the impulses in the images. Given a set of N real-valued feed-back coefficients $A_i\Big|_{i=1}^{N}$ and a set of $M+1$ real-valued feed-forward coefficients $B_i\Big|_{i=1}^{M}$ the $M+N+1$ RWM filter output is given by

$$Y(n) = median(|A_N| \lozenge \operatorname{sgn}(A_N) y(n-N)|, \ldots, A_l| \lozenge \operatorname{sgn}(A_N) y(n-N), |B_0| \lozenge \operatorname{sgn}(B_0) X_n, \ldots, |B_M| \lozenge \operatorname{sgn}(B_M) X(n+M))$$

Where $\langle (A_N,...,A_1,B_0,B_1,...,B_M) \rangle$ are the coefficients of recursive weighted median filter [14].

4.1 Adaptive Window Size Selection

Generally in the filters of small window size, the amount of filtered noise density will be very less while the window size of the filter may increase for filtering high density noise. This may lead to blurring in the output images. In order to overcome this, the adaptive window length filters are designed for filtering high density noises. Hence selecting window size is very important for noise detection. In the proposed filter SWAM, selection of the adaptive window size is made first based on both the intensity value of the pixels and the amount of noises present in the input signal. On applying RWM filter to the output image $y(i,j)$ as defined in equation (1), the window size of the image is calculated. Due to this, the unwanted filtering of uncorrupted pixels is reduced. Therefore, blurring is reduced even at high density noise. The weights are chosen by median controlled algorithm in accordance with the above length [14].

Steps involved in the Median controlled algorithm are as follows:

1. Get the median filtered image using the window sliding W and store the result in reference image.
2. Calculate the weight as $\text{Weight}\ i,j = \exp\{-\alpha \,|\, \text{original}\ i,j - \text{Reference}\ i,j\ |\}$ 3. Using the above weights, perform the Recursive weighted median operation and store the output as reference image.
4. The process is done iteratively, so that output image is produced with least mean square error.

This output image which is produced with least mean square error is considered as an input image for the second stage where impulse noise detection mechanism is implemented.

5. IMPULSE NOISE DETECTION

The impulse detection is usually based on the following two assumptions: 1) a noise-free image consisting of locally smoothly varying areas separated by edges and 2) a noisy pixel having very high or very low gray value compared to its neighbours. During the impulse reduction procedure two image sequences are generated. The first is the sequence of gray scale image $\{x^{(0)}_{(i,j)}, x^{(1)}_{(i,j)}, x^{(2)}_{(i,j)},..., x^{(n)}_{(i,j)}\}$ where the initial image $x^{(0)}_{(i,j)}$ is noisy image itself, (i, j) is position of pixel in image, where $1 \le i \le M, 1 \le j \le N$, M and N are number of pixels in horizontal and vertical directions respectively and $x^{(n)}_{(i,j)}$ is image after nth iteration. The second is the binary flag image sequence $\{f^{(0)}_{(i,j)}, f^{(1)}_{(i,j)}, f^{(2)}_{(i,j)},..., f^{(n)}_{(i,j)}\}$ where the binary flag $f^{(n)}_{(i,j)}$ is used to indicate whether the pixel at *(i, j)* in noisy image detected as noisy or noise-free after n^{th} iteration. If $f^{(0)}_{(i,j)} = 0$ means pixel at (i, j) has been found as noise-free after n^{th} iteration and if $f^{(n)}_{(i,j)} = 1$ means pixel at (i, j) has been found as noisy after n^{th} iteration. For the selected window size the value of $x^{(n)}_{(i,j)}$ is modified and given by,

$$x^{(n)}_{(i,j)} = \begin{cases} m^{(n-1)}_{(i,j)} \text{ if } f^{(n)}_{(i,j)} \ne f^{(n-1)}_{(i,j)} \\ x^{(n-1)}_{(i,j)} \text{ if } f^{(n)}_{(i,j)} = f^{(n-1)}_{(i,j)} \end{cases}$$

After noise detection, only binary flag image is required for noise filtering process. The elements of this image give information about whether the pixel is corrupted or not at location (i, j) in noisy image $x^{(0)}_{(i,j)}$. If (i, j)th image has detected as a noise then it will go through median filtering process otherwise it will remain the same which is called Switching based Median Filter [8].

6. ALGORITHM FOR THE PROPOSED SWITCHING WEIGHTED ADAPTIVE MEDIAN (SWAM) FILTER

The SWAM filtering technique has two stages. In the first stage the adaptive window size for the output image $y(i,j)$ as defined in equation (1) is obtained by using RWM filter. Also a weight adjustment is made to central pixel $x(i,j)$ within the size of the sliding window obtained on using median controlled algorithm. As RWM filter uses the intensity value of the pixels the unwanted filtering of uncorrupted pixels as well as blurring is reduced even at high noise density level. In second stage for the output image which was produced by RWM filter with least mean square error is considered as input image for the detection mechanism.

Algorithm:

Input: Noisy image (Reference Image of first stage)

Step 1: To detect the impulse noise.

The detection of noisy and noise free pixels is decided by checking whether the value of a processed fixed element $I(x,y)$ lies in the range $|I_{\max} - I_{\min}|$ or not, as the impulse noise pixel can take a maximum and minimum value in the dynamic range (0,255) . If the value lies within this range then it is uncorrupted pixel and left unchanged. Otherwise, it is a noisy pixel and is replaced by the median value of the window or by its neighborhood.

Step 2: On applying adaptive median filtering to the corrupted image yields a filtered image and a binary flag image $\{f(i,j)\}$ given by,

$$f^{(n)}_{(i,j)} = \begin{cases} f^{(n-1)}_{(i,j)} if \left| X^{(n-1)}_{ij} - m^{(n-1)}_{ij} \right| < T \\ 1, \quad \text{otherwise} \end{cases}$$

where T is pre-defined threshold value. The impulse detection scheme detects noise even at high corruption level setting flag matrix value as 1 wherever noise exists.

Step 3: Find on how many pixels are detected as noisefree in current filtering window with respect to the corresponding binary flag window [14].

Step 4: Extend window size outward by one pixel on all the four sides of the window if the number of uncorrupted pixels is less than ¼th of the total number of pixels within filtering window. Repeat the above steps until the end of the image is reached.

Step 5: The pixels that are classified as noisefree in filtering window will continue in median filtering process and the other pixels which are noisy cannot continue in filtering process. This will yield a better filtering result with less blurring and distortion.
Output: Denoised Filtered Image.

7. SIMULATION RESULTS

The performance of the proposed algorithm is tested with different gray scale images (Lena) and with their dynamic range of values [0,255]. 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%. The performance evaluations of the filtering operation are quantified by the PSNR and Image Enhancement Factor (IEF).

$$PSNR = 10\log_{10}\left(\frac{255^2}{MSE}\right)$$

$$MSE = \frac{1}{MN}\sum_{ij}(I_{ij} - \hat{I}_{ij})^2$$

where I_{ij} , $\hat{I}_{ij}$ are the original and filtered images, $M \mathrm{X} N$ size of the image.

$$IEF = \frac{\sum_{ij}(\eta_{ij} - I_{ij})^2}{\sum_{ij}(\hat{I}_{ij} - I_{ij})^2}$$ Where η_{ij} is corrupted image.

The restoration performance is assessed according to the noise density of the corrupted pixels in the Lena image. Both $PSNR$, IEF measure the difference in the intensity values of a pixel in original and enhanced images. These values are calculated for the proposed algorithm and a comparison performance with various filters SMF,AMF,WMF,RWM are shown in Table-1 & Table-2. The corresponding values are plotted in figure (2) and figure (3). From the plot, it is observed that the proposed filter exhibits better performance in comparison with other filters. In the proposed filter, the problem of blurring of images for large window size and poor noise removal for smaller window size are overcome by selecting the length of the adaptive window size appropriately. Also, the output image produced in the first stage which is partially denoised with least mean square error is used as input image for noise detection process. Due to this the unwanted filtering of uncorrupted pixels and blurring are reduced at high noise density level.

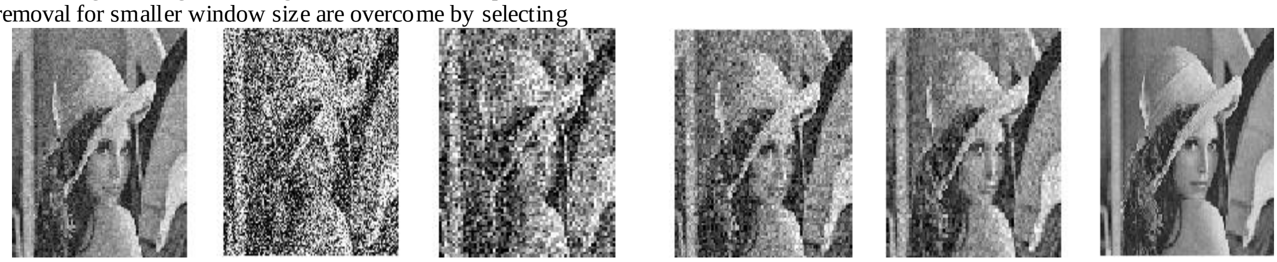
Table 1. Performance Analysis PSNR in DB for Various Filters for Lena

NOISE (%)	SMF	AMF	WMF	RWM	SWAM
0.02	31.05	29.48	34.22	33.28	35.7694
0.04	27.98	28.30	27.08	32.22	35.1338
0.06	23.18	27.10	21.66	31.08	34.5218
0.08	18.68	25.50	17.57	28.14	33.8229
0.10	15.06	24.04	14.22	25.96	32.9060
0.12	12.19	21.07	11.64	21.88	32.1894
0.14	9.79	16.10	9.49	17.56	31.7232
0.16	7.93	11.60	7.90	14.14	31.1196
0.18	6.44	8.002	6.58	11.91	30.7168

Table 2. Performance Analysis IEF for Various Filters for Lena

NOISE (%)	SMF	AMF	WMF	RWM	SWAM
0.02	19.21	25.44	20.34	15.39	22.3732
0.04	40.60	38.89	56.25	44.76	37.9566
0.06	51.33	43.32	36.31	75.37	48.6988
0.08	30.33	41.24	30.44	89.12	55.6770
0.10	14.44	36.69	20.95	87.72	55.1275
0.12	6.76	21.90	9.32	67.29	56.5134
0.14	3.55	8.14	3.94	32.14	59.4644
0.16	2.04	3.29	1.65	12.96	60.7013
0.18	1.36	1.62	1.39	3.40	60.9378

For qualitative analysis performance of the filters are tested at 80% of noise density and the results are shown in Figure 2, 3 and 4.



(a) (b) (c) (d) (e) (f)

Fig 2: Simulation results for different filters (a) Original image, (b) Output for SMF (c) Output for AMF (d) Output for WMF (e) Output for RWMF (f) Output for SWAM

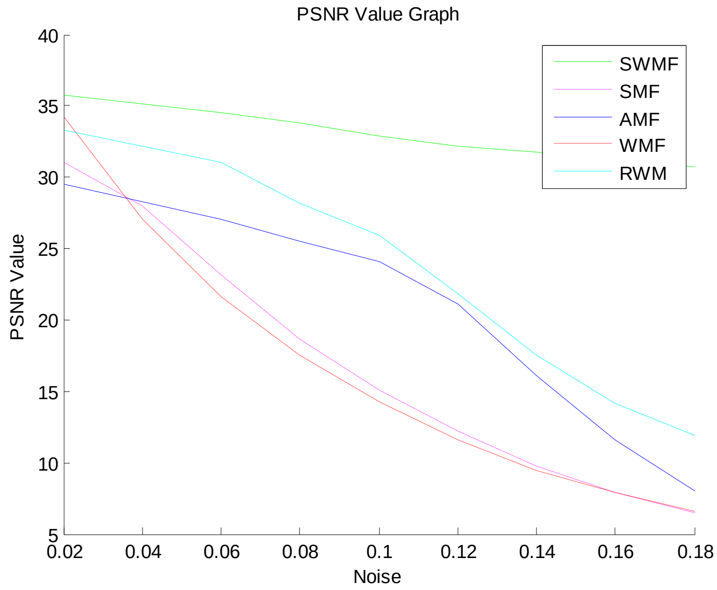


Fig 3: Plot of Noise Vs PSNR Value

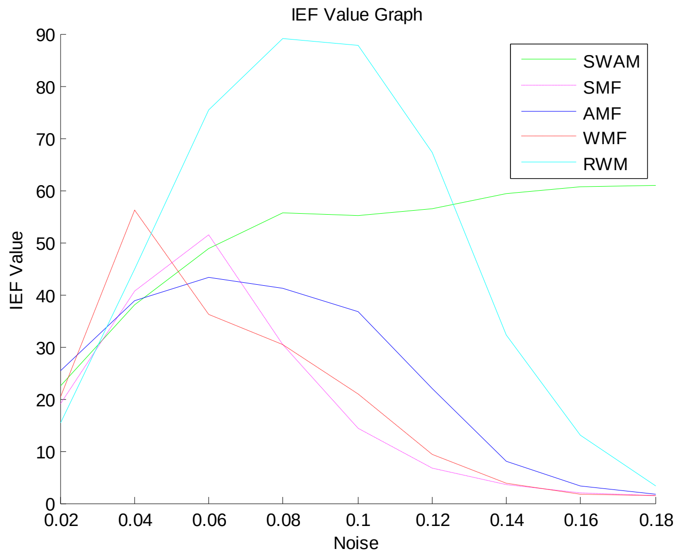


Fig 4: Plot of Noise Vs IEF

8. CONCLUSION

To demonstrate the performance of the proposed method extensive experiments have been conducted on a standard test image to compare our method with many other well known techniques. The proposed filter is designed where the window length is determined appropriately based on the width of the impulsive noise presented in the input signal and the uncorrupted pixel is not filtered. Also the weights of the filter are calculated by using the median controlled algorithm. Due to this the results are very effective the resulting image, will have less blurring in the output signal. The results reveal that the proposed SWAM filter exhibits better performance in terms of PSNR and IEF. The SWAM filter also shows consistent and stable performance across a wide range of noise densities varying from 10% to 90% densities.

9. REFERENCES

[1] G.Arce, J.Paredes, 2000. Recrusive weighted median filters admitting negative weights and their optimization, IEEE Trans.signal proc. 49.

[2] Bovi, 2000. Handbook of image and video processing New York, Academic.

[3] R.H.Chan et al 2005. Salt and pepper noise removal by median type noise detection and detail processing regulations IEEE Trans.Image Process. 14, 1479-1485.

[4] H.I.Eng, K.K.Ma, 2001. Noise adaptive soft switching median filter IEEE Trans. Images process. 10, 242–251.

[5] Ho Ming et al, 1998. Median filters with adaptive length IEEE Transcations of the circuits and systems, 35.

[6] T.S Huang et al, 1979. Fast two dimensional median filtering algorithm, IEE Trans. Acoustics Speech Signal Process ASSP, 1, 13–18.

[7] H.Hwang and R.A Hadaad, Adaptive Median filters new algorithms and results IEEE Trans. On image processing 4, 499–502.

[8] Mamta Juneja, Rajni Mohana, 2009. An improved adaptive median filtering method for impulse noise detection International Journal of Recent Trends in Engg. 1.

[9] S Manikandan et al, 2004. Adaptive length recursive weighted median filter with improved performance in impulsive noisy environment, WSEAS transaction on Electronics, issue3, 1.

[10] Nicklova, 2004. A variational approach to remove outlines and impulse noise Journal of Mathematical imaging and risson. 20, 99–120.

[11] I.Pitas and A.N Venetsanopoulos, 1990. Nonlinear Digital Filters Principles and Applications, Norwell MA .Kluwer.

[12] G.Pok and J.C.Liu, 1999. Decision based median filter improved by predictions in proc. ICIP. 2, 410–413.

[13] C.A Pomalaza-Raz, C.D. Macgillem,1984. An adaptive non linear edge preservering filter IEEE Trans Acoust. Speech Signal Process ASSP -32, 571–576.

[14] V.R VijayKumar et al, 2008. Adaptive window length Recrussive weighted median filter for removing impulse noise in images with details preservation.ECTI Transactions on Electrical Eng.Elect.and Communications, 6.

[15] Z.Wang, D.Zhang, 1999. Progressive switching median filter for the removal of impulse noise from highly corrupted images, IEEE Trans. On circuits and systems 11.46, 78–80.

[16] S.Zhang, M.A Karim, 2002. A new impulse detector for switching median filter IEEE signal process Lett. 9, 360–363.

[17] Rajoo Pandey,2008, An improved switching median filter for uniformly distributed impulse noise removal, World Academy of Science Engineering and Technology 38