Adaptive Window Length Recursive Weighted Median Filter for Removing Impulse Noise in Images with details Preservation

V.R.Vijay Kumar [1], **S.Manikandan** [2], **P.T.Vanathi** [3], **P.Kanagasabapathy** [4], and **D.Ebenezer** [5], Non-members

ABSTRACT

An adaptive window length Recursive Weighted Median filter [ARWMF] for removing the impulse noise with better edge and fine detail preservation is presented. Larger window size may blur the images and the lower window size does not remove the noise at high density. To overcome this, the window size of the RWMF is adaptive based on the presence of noise density. Median controlled algorithm is used to calculate the weights for the RWMF. In median controlled algorithm, the filter gives the smallest weight for the impulse. However, for many weight functions, including the exponential one, this weight is non-zero. Thus the impulse has an effect on the output and the magnitude of the impulse is reduced. The computational complexity for the weight calculation is simple and it is very efficient. The window size of the RWMF is adaptive based on the presence of noise density. The proposed algorithm produces better edge and fine details preservations and reduces blurring at the high density impulse noise.The performance of the proposed algorithm is given in terms of mean square error (MSE), mean absolute error (MAE) and peak signal to noise ratio (PSNR) and it is compared with Standard Median filters, Weighted Median filters, Center Weighted Median filters, Recursive Weighted Median filters and Lins Adaptive length Recursive weighted median filters using Median Controlled Algorithm.

Keywords: Adaptive Window size, High Impulse Noise suppression, Less computation, Median controlled Algorithm, Recursive weighted median filter.

1. INTRODUCTION

I mpulse noise is caused by malfunctioning pixels in camera sensors, faulty memory locations in hardware, or transmission in a noisy channel. Two common types of impulse noise are the salt-and-pepper noise and the random-valued noise. For images corrupted by salt-and-pepper noise (respectively random-valued noise), the noisy pixels can take only the maximum and the minimum values (respectively any random value) in the dynamic range. There are many types of impulse noise. Let Y_{ij} be the gray level of a true image Y at pixel location (i, j) and $[n_{min}, n_{max}]$ be the dynamic range of Y. Let X_{ij} be the gray level of the noisy image X at pixel (i, j), then the impulse noise model is given as equation 1

$$\begin{aligned} X_{ij} &= R_{ij} \text{ ; with probability } r; \\ & Y_{ij} \text{ ; with probability } 1-r; \end{aligned} \quad (1)$$

where $R_{ij} \in [n_{min}; n_{max}]$ are random numbers and r is the noise ratio. For example, for fixed-valued (salt-and-pepper) impulse noise, noisy pixels X_{ij} take either n_{min} or n_{max}. There are many works on the restoration of images corrupted by impulse noise. The median filter was once the most popular nonlinear filter for removing impulse noise, because of it's good denoising power and computational efficiency. Over the last two decades, there is a significant improvement in the development of median filters. Weighted median filter (WMF) [3], RWM[4] filter are examples. However, when the noise level is over 50%, some details and edges of the original image are smeared by the filter. Different remedies of the median filter have been proposed, e.g. [1],[2],[12]the adaptive median filter, the multi-state median filter, or the median filter based on homogeneity information. These so-called "decision-based" or "switching" filters [9][10][11] first identify possible noisy pixels and then replace them by using the median filter or its variants, while leaving all other pixels unchanged. These filters are good at *detecting* noise even at a high noise level. Their main drawback is that the noisy pixels are replaced by some median value in their vicinity without taking into account local features such as the possible presence of edges. Hence details and edges are not recovered satisfactorily, especially when the noise level is high. It has been proved that RWM [4] filter produces better result when compared to other median type filter. The median type filters exhibit blurring for fixed window sizes and insufficient noise suppression for

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[1,3] The authors are with Department of ECE, PSG College of Technology, India, E-mail: vr_vijay@yahoo.com
[2,5] The authors are with Department of ECE, SKCET, India, E-mail: mani567@yahoo.com
[4] The author is with 4Dean, Madras Institute of Technology, India, E-mail:

small window sizes. In this paper an adaptive window size RWM filter algorithm using median controlled algorithm is proposed, which achieve a high degree of noise suppression and preserve image sharpness. Lin's, & Huang proposed adaptive length median filters for removal of impulse noise in images. Adaptive length Recursive weighted median filter using Lin's algorithm produces less efficient output and the algorithm has high complexity. In case of adaptive RWM filter [4], the weights are chosen in accordance with window length. In some windows the signal may be noise free. However attenuation of the amplitude of the signal causes blurring. Window lengths are selected based on the amount of noises present in the input signal. After calculating the window length, the RWM operation is performed. The weight for the proposed adaptive RWM filter is calculated by using the median controlled algorithm. This algorithm is simple and has less computation and less complexity compared to the other weight calculating algorithms. And also the proposed algorithm is simple and produces better PSNR, MSE and MAE compared to the other standard algorithms.

2. RECURSIVE WEIGHTED MEDIAN FILTER

The success of the median filters in the image processing is based on two intrinsic properties: edge preservation and efficient attenuation of the impulsive noise properties not shared by traditional filters. The application of the weighted median filters, however, has not significantly spread beyond image processing applications. When a median type filter filters a signal, some characteristic(s) will change. But impulse noise will be reduced significantly. In general, changes are more profound nearer edges than homogeneous regions. Thus the median filter can be understood as a simple detector of impulses and edges. It is a highly data dependent filter, by which weights have been given to the samples according to the changes by the low pass filter. The recursive weighted median filter detects and remove the impulses in the images. The general structure of linear IIR filters is denoted by the equation 2

$$Y(n) = \sum_{l=1}^{N} A_l Y(n-1) + \sum_{k=-M_1}^{M_2} B_k X(n-k) \quad (2)$$

where the output is formed not only from the input, but also from previously computed outputs. The filter weights consist of two sets: the feedback coefficients $\{A_l\}$, and the feed-forward coefficients (B_k). N +M1 +M2 + 1 coefficient are needed to denote the recursive difference equation. For WM filters, the summation operation is replaced with the median operation, and the multiplication weighting is replaced by signed replication as in equation 3

$$\begin{aligned} Y(n) \;&=\; Median(|A_l| \diamond sgn(A_l)Y(n-l)|_{L=1}^{N} \\ &\quad |B_k| \diamond (B_k)X_{n-k}|_{k=-M_1}^{M_2}) \end{aligned} \quad (3)$$

2.1 Recursive Weighted Median Filters

Given a set of N real-valued feed-back coefficients $A_i |_{i=1}^{N}$ and a set of M+1 real-valued feed-forward coefficients $B_i |_{i=0}^{M}$, the M+N+1 recursive WM filter output is defined as equation 4.

$$\begin{aligned} Y(n) \;&=\; Median(|A_N| \diamond sgn(A_N)Y(n-N)|, \ldots \\ &\quad |A_l| \diamond sgn(A_N)Y(n-1), |B_0| \diamond sgn(B_0)X_n, \\ &\quad \ldots |B_M| \diamond sgn(B_M)X(n+M)) \end{aligned} \quad (4)$$

where $< (A_N, \ldots A_1, B_0, B_1, \ldots B_M) >$ are the coefficients of recursive weighted median filter.

2.2 Adaptive window size Selection

Generally in the fixed small window size filters, the amount of noise density filtered will be very less, for filtering high density noise the window size of the filter may increase. 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. The proposed algorithm is simple and has less computation. Lin [1] and Huang [12] proposed some adaptive algorithms for filtering impulse noise. But these algorithms are more complex and the results are not better compared to the proposed adaptive algorithm. In case of Lin's algorithm, based on the threshold values the window size is selected but in the proposed algorithm there is no need to calculate the threshold values. The proposed adaptive technique uses the intensity value of the pixels, to determine whether the pixel is corrupted or uncorrupted pixel. And based on the amount of corrupted pixels, the window size is increased or decreased. Due to this, the unwanted filtering of uncorrupted pixels is reduced. And hence blurring is reduced even at high density noise.

2.3 Median Controlled Algorithm

The weight calculation for the Recursive WM filter is performed by threshold decomposition technique, optimal weights by MAE technique for real weight calculation, Complex weights calculation and negative weights calculation. The above method is complex and has high computation. Mean square error and mean absolute error are used for calculating the weights for the RWM filters in optimization techniques. The original image is needed for the calculation of MSE and MAE. And also, the weights calculated by the optimization technique may be zero and negative. In case of median controlled algorithm, the selection of weights is simple and also the filter gives small weights for the impulse. For example, for each window, those input samples which are closer to the output of the first filtering operation can be exponentially weighted more. Let the difference of the sample X_i and the result of the low pass filtering X'_i at the same position be $|X_i\text{-}X'_i|$. Weight values can be obtained by using the equation 5

$$Weight(i,j) = \exp\{-\alpha\ |original(i,j) - reference(i,j)|\} \quad (5)$$

Where $\alpha > 0$. The output of the first iteration of the median controlled filter is obtained as a weighted sum of the samples inside the moving window of the filter. This moving window need not be the same window that is used in the calculation of weights. The general weighted median filter structure [3] with weights as $a=(a_1,a_2,a_3\ldots a_i)$ and the inputs $x=(X_1,X_2,X_3\ldots X_i)$ is given by Weight $Med(X_1,X_2,X_3\ldots X_i)=MED\{(a_1\diamond X_1,a_2\diamond X_2,a_3\diamond X_3\ldots a_i\ X_i)\}$ Where $\diamond$ is the replication operator defined as $a_i\diamond X_i=(a_i,\ a_i\ldots a_i)$ Xi times[3] Selecting the output of the first iteration to be the reference signal, computing the new weights by comparing the new reference signal to the original signal, and computing the output again using the new weights can continue the procedure. This is repeated until the number of the iterations is reached. Thus the Median controlled Recursive Weighted Median filter is obtained. One needs only to change the first Reference signal calculation to be done by the Recursive weighted median filter with weights a_i.

This gives more freedom for the designer. Further more, one can completely reject potential outliers by letting the weights be zero when the difference between the filtered signal and the original signal exceeds a certain level.

Steps involved in the Median controlled algorithm are as follows

1. Get the median filtered image using the window sliding W, store the result in REFERENCE image.
2. Calculate the weight as
   Weight(i,j)= $\exp\{-\alpha|original(i,j)$ - $Reference(i,j)|\}$
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.

3. STRUCTURE OF THE FILTER

The general structure of the recursive weighted median filter [4] is given as equation 6,

$$\begin{aligned} Y(n) &= MED(|A1| \diamond sgn(A1)Y(n-1)^N| \\ &\quad + Bk| \diamond sgn(X(n+k)^{M_2})) \end{aligned} \quad (6)$$

Let us consider the algorithm as stages as shown in the block diagram (Fig 1).

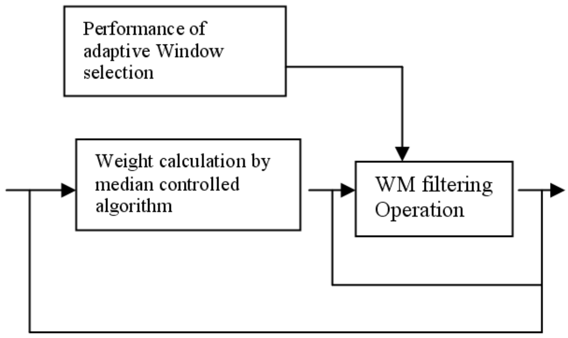


Fig.1: *Block diagram of Median controlled adaptive RWM filter*

Stage 1: Determination of the window size:

Z_{min} = minimum intensity value in S_{xy}
Z_{max} = maximum intensity value in S_{xy}
Z_{RWM} = RWM intensity value in S_{xy}
Z_{xy} = intensity value at coordinates S_{xy}

The adaptive Recursive weighted median filtering algorithm works in two levels

Level A : If $Z_{min} < Z_{RWM} < Z_{max}$, go to level B
Else increase the window size
If window size $\leq S_{max}$, repeat level A
Else output Z_{RWM}
Level B : If $Z_{min} < Z_{xy} < Z_{max}$, output Z_{xy}
Else output Z_{RWM}

Stage 2: Filtering operation:

The Recursive weighted median filtering operation is carried out based on the adaptive window size determined. The algorithm for the recursive weighted median filter is given as:

Input s/ Outputs : $M \times N$ image
Moving window W, |W|=N=2k+1
Weight vector $a=(a_1,\ a_2\ldots a_N)$
Let Half Sum= $\sum_i^N = 1\ a_i\ /2$
for i=1to Number of Rows
    for j=1 to Number of Columns
        place the window W at (i,j)
        store the image values inside W and the corresponding
        weights in x= ((X1,a1),(X2,a2),...(XN,aN))
        sort x with respect to Xis, store the result in
        y = ((X1,a1),(X2,a2),...(XN,aN))
        let Sum = 0, m =1
        repeat
        let Sum = Sum+a(m)
        let m= m+1
        until Sum ≥ Half Sum
        let Output(i,j) = y(m-1)
        Recmed(X1,X2,...XN) =
        MED(Y1,Y2,...Yk,Xk+1,...XN)
    end
end

3.1 RESULTS

In MATLAB7.1 the proposed ARWM filter using median controlled algorithm is tested using the Gray scale images (Elaine, Lena and Pepper) and colour (Zelda) image. Fig2 show the results Elaine image corrupted by 20% of noise density. Fig 2 (a, b, c, d, e, f, g) are the original image, corrupted image, standard median filter (SMF) output, Weighted median filter (WMF) output, Recursive Weighted median filter (RWMF) output, Median controlled using Lin's algorithm (MC Lin's) output and the proposed ARWMF using median controlled algorithm. Fig3 show the results of Lena image corrupted by 60% of noise density and results of the different filters. Fig 4 (a, b, c, d, e, f, g, h) are the original pepper image, corrupted image at 90% noise density, standard median filter (SMF) output, Center Weighted median filter (CWMF) output, Weighted median filter (WMF) output, Recursive Weighted median filter (RWMF) output, Median controlled using Lin's algorithm (MC Lin's) output and the proposed method output. Fig.5 shows the Zelda original color image corrupted by 60% noise density and restored results of various filters. For colour image, the proposed algorithm is applied to each plane (R, G, and B) separately and later the outputs are combined. The performance metrics such as Peak signal to noise ratio (PSNR), Mean square error (MSE) and Mean absolute error (MAE) are evaluated using the following formulas

$$PSNR = 10\log_{10}\left(\frac{225^2}{MSE}\right) \quad (7)$$

$$MSE = \frac{1}{MN}\sum_{ij}(y_{ij} - x_{ij})^2 \quad (8)$$

$$MAE = \frac{1}{MN}\sum_{ij}|y_{ij} - x_{ij}| \quad (9)$$

For color image the equation of MSE and MAE is multiplied by a factor 1/3. From the results, at the higher noise densities the proposed adaptive recursive weighted median filter produces better results. The edges and fine details are preserved without blurring clearly shown in the visual results.

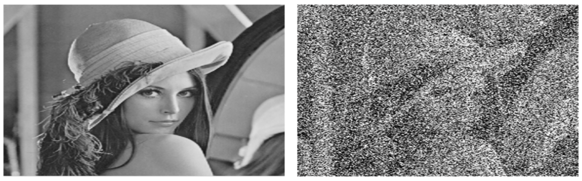
(a) (b)

(c) (d)

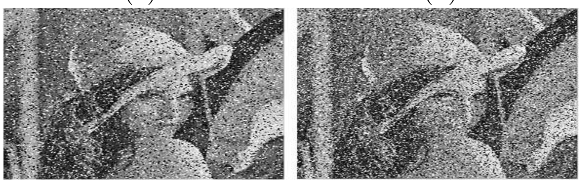
(e) (f)

(g) (h)

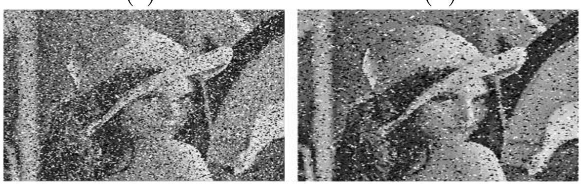
Fig.2: *(a) Original 512x512 Elaine image (b) Noisy image (Noise Density =20%) Outputs of(c)SMF (d) CWMF (e) WMF (f) MC with Lin's AW (g) RWMF (h) Proposed Method*



(a) (b)



(c) (d)



(e) (f)

(g) (h)

Fig.3: *(a) Original 512X512 lena image (b) Noisy image (Noise Density =60%). Outputs of(c)SMF (d) CWMF (e) WMF (f) MC with Lin's AW (g) RWMF (h) Proposed Method*

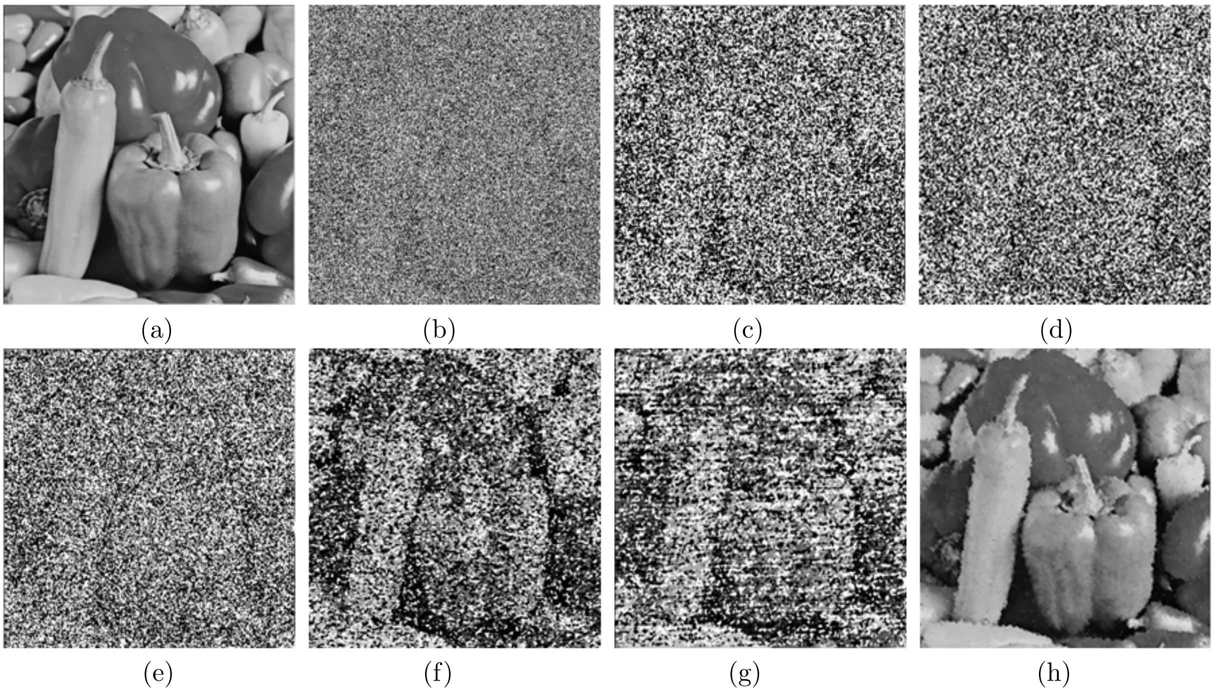


Fig.4: *(a) Original 256X256 Pepper Image (b) Noisy Image (Noise Density=90%). Outputs of (c) SMF (d) CWMF (e) WMF (f) MC with Lin's AW (g) RWMF (h) Proposed Method*

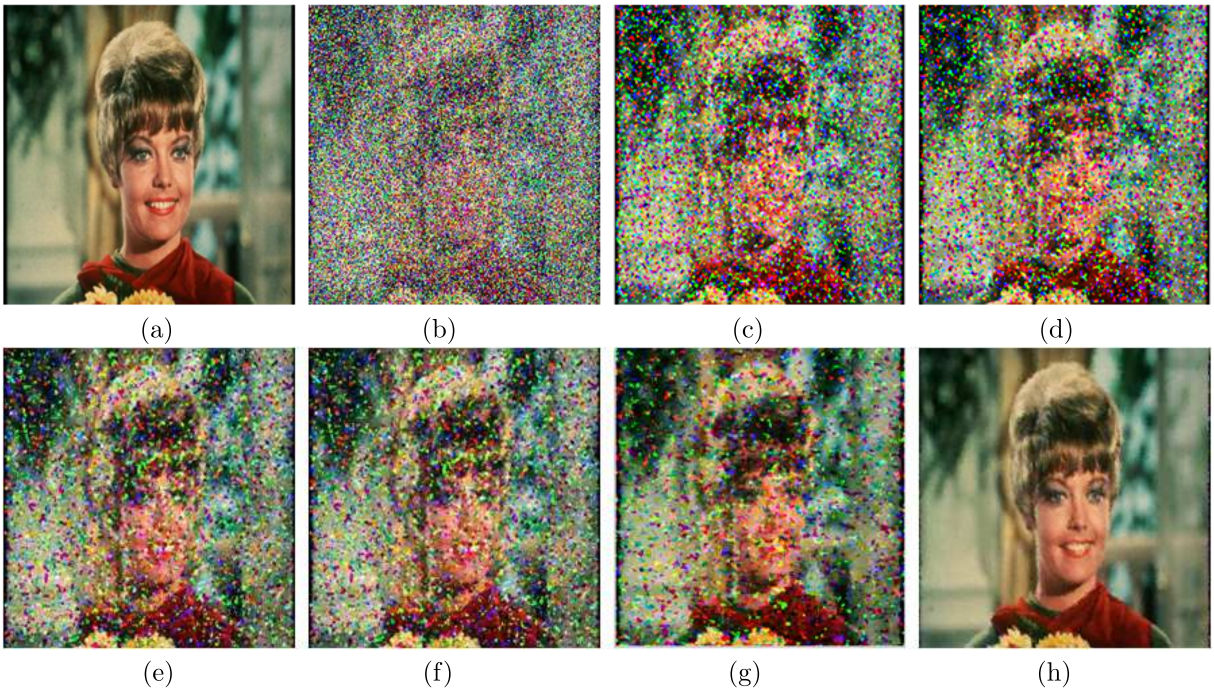


Fig.5: *(a) Original 256X256 Zelda Image (b) Noisy Image (Noise Density=60%). Outputs of (c) SMF (d) CWMF (e) WMF (f) MC Lin's (g) RWMF (h) Proposed Method*

Table 1: *Comparison table of PSNR of different filters for Lena.png (Gray scale Image)*

Noise Density	SMF	CWMF	WMF	MC Lin's	RWM	Proposed Algorithm
10	33.72	33.67	34.22	34.48	33.28	29.29
20	29.62	25.81	27.08	31.70	32.22	28.52
30	24.03	20.04	21.66	27.53	31.08	28.09
40	19.03	16.19	17.57	22.30	29.14	27.19
50	15.45	13.12	14.22	17.40	25.96	26.71
60	12.44	10.59	11.64	13.72	21.88	26.22
70	10.09	9.12	9.49	10.70	17.56	25.63
80	8.19	7.64	7.90	8.36	14.14	24.22
90	6.69	6.46	6.58	7.91	11.91	22.97

Table 2: *Comparison table of MSE of different filters for Lena.png (Gray scale Image)*

Noise Density	SMF	CWMF	WMF	MC Lin's	RWMF	Proposed Algorithm
10	25.90	21.16	20.3401	27.24	18.83	35.76
20	46.10	76.56	56.25	41.99	40.32	36.60
30	117.50	228.91	179.56	76.03	88.54	79.74
40	305.20	561.69	444.3664	184.96	174.24	83.53
50	677.04	1101.57	895.8049	466.56	237.16	105.47
60	1330.06	1882.69	1586.429	1041.99	517.56	125.66
70	2241.07	3028.30	2524.058	1993.62	1203.39	137.35
80	3464.5	3913.75	3672.36	3425.76	2127.05	147.37
90	4883.21	5162.42	5031.065	4956.16	4406.30	254.72

Table 3: *Comparison table of MAE of different filters for Lena.png (Gray scale Image)*

Noise Density	SMF	CWMF	WMF	MC Lin's	RWM	Proposed Algorithm
10	2.74	1.72	2.12	1.08	1.48	4.51
20	3.40	3.08	3.17	1.93	1.68	5.53
30	5.06	6.67	5.70	3.15	1.94	5.85
40	9.10	13.21	10.75	5.79	2.40	6.10
50	16.39	24.05	19.87	12.06	3.42	6.49
60	28.92	38.18	33.45	23.63	5.73	6.71
70	46.68	56.78	52.44	42.88	11.23	7.37
80	70.01	78.18	73.9	69.61	20.76	8.59
90	96.98	101.66	99.01	94.26	31.45	10.84

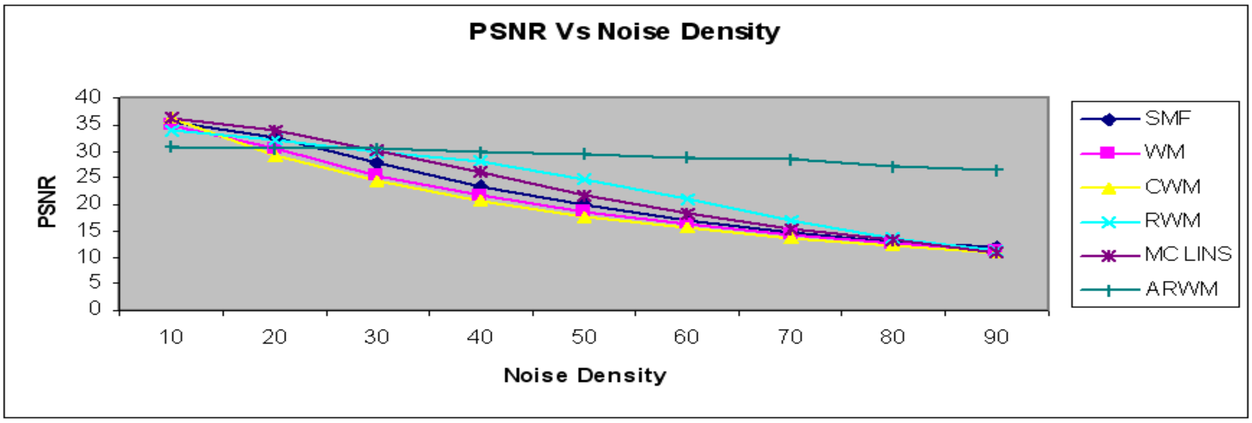


Fig.6: *Comparison graph of PSNR at different noise density of Zelda image*

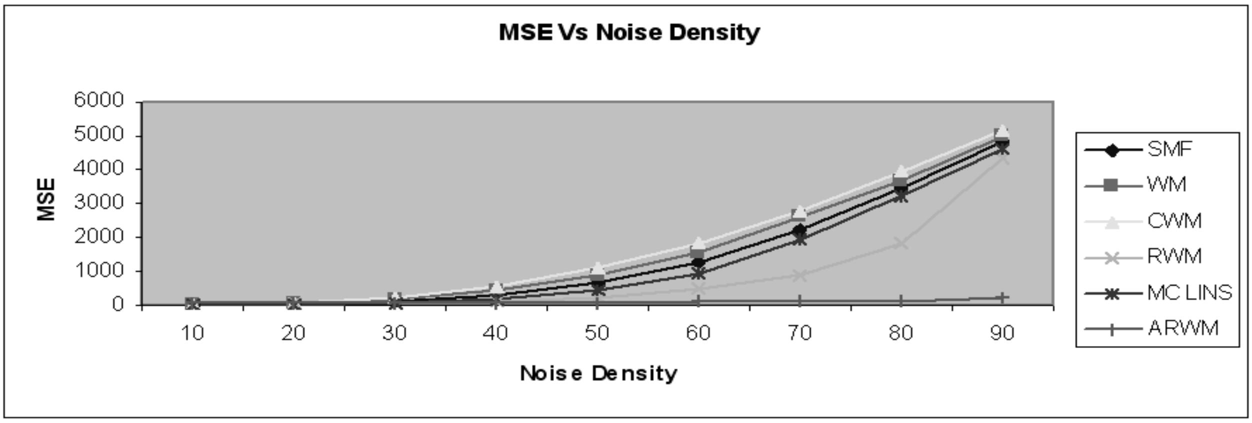


Fig.7: *Comparison graph of MSE at different noise density of Zelda image*

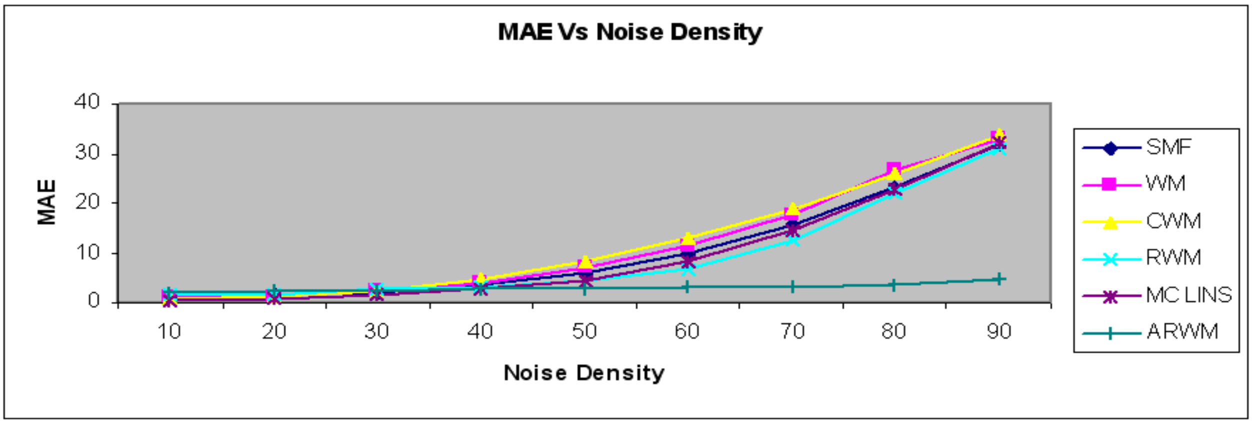


Fig.8: *Comparison graph of MAE at different noise density of Zelda image*

4. CONCLUSION

Generally, the RWM filters are designed only for the fixed window length. This causes blurring in the output samples. Because in the fixed window length, the noise may absent in some windows in that condition, the filtering operation is done for the original samples which causes the blurring in the output. To overcome the problem, this filter is designed where the window length is determined by the width of the impulsive noise presented in the input sample. Hence, there is no chance of filtering the uncorrupted pixel and it reduces the blurring in the output sample. And the weights calculated by using the median controlled algorithm is producing very effective result and causes less blurring and the MSE and MAE are also very less when compared to other median type algorithms. But the proposed algorithm has three different stages for compute the result and hence the processing time is more compare to the existing methods.

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V.R.Vijaykumar is currently working as a lecturer in the department of Electrionics and Communication Engineering, PSG College of Technology, Coimbatore. He received his bachelor degree from Government of college of Technology, Vellore and Master degree from Thiagarajar college of Engineering, Madurai. He is currently doing his Ph.D under Anna University, Tamilnadu. His research interest is digital image processing, nonlinear filters, and digital signal processing.

S.Manikandan received his bachelor degree from Madras University and Master degree from Anna University. His area of interest includes nonlinear signal processing, VLSI design and image processing. He is currently working as lecturer in the department of Electronics and Communication Engineering, Srikrishna college of Engineering and Technology, Coimbatore.

P.T. Vanathi is working as Assistant Professor in the department of Electronics and Communication Engineering, PSG College of Technology, Coimbatore. Her area of interest includes Speech Signal Processing, Non linear signal processing, Digital communication and VLSI Design. She has published many papers in international journals and international conferences. She is also member of review committees for many national and international conferences.

P.Kanagasabapathy is working as Dean, Madras Institute of Technology, Anna University. His area of interest includes Speech Signal Processing, Digital Image Processing, and Process Control Instrumentation. He has published many papers in international journals and international conferences. He is also member of review committees for many national and international Journals.

D. Ebenezer is currently working as a professor in the department of Electronics and Communication Engineering, Srikrishna college of Engineering and Technology, Coimbatore. He worked as a Assistant .Professor in College of Engg. Guindy, Anna University. His area of interest includes Digital signal processing, Non-linear signal processing, Digital communication. He has published many papers on Non Linear signal processing. And he is also member of review committees for many national and international conferences.