High Density Impulse noise Removal in Color Images Using Median Controlled Adaptive Recursive Weighted Median Filter

V.R.Vijay Kumar, S.Manikandan, D.Ebenezer, P.T.Vanathi and P.Kanagasabapathy

***Abstract*—** An adaptive varying window size Recursive Weighted Median filter [ARWMF] for removing the impulse noise in Color images is presented. The weights for the RWMF is calculated by using the Median controlled algorithm. The computational complexity for the weight calculation is simple and it is very efficient. 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 window size of the RWMF is adaptive based on the presence of noise density. 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.

I. INTRODUCTION

Impulse 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 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 its 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](Arce.G), 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 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 cause 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.

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II. 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 detect and remove the impulses in the images. The general structure of linear IIR filters is denoted by the difference equation

$$Y(n) = \sum_{\ell=1}^{N} A_\ell \, Y(n-\ell) + \sum_{k=-M_1}^{M_2} B_k \, X(n-k)$$

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 coefficients are needed to denoted 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:

$$Y(n) = \text{MEDIAN}\Big(|A_\ell| \diamond \text{sgn}(A_\ell) Y(n-\ell)|_{\ell=1}^{N}, \; |B_k| \diamond \text{sgn}(B_k) X(n-k)|_{k=-M_1}^{M_2}\Big)$$

A. *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

$$\begin{aligned} Y(n) = \text{MEDIAN}(&|A_N| \diamond \text{sgn}(A_N) Y(n-N), \cdots, \\ &|A_1| \diamond \text{sgn}(A_1) Y(n-1), \; |B_0| \diamond \text{sgn}(B_0) X(n) \\ &\cdots, \; |B_M| \diamond \text{sgn}(B_M) X(n+M)). \end{aligned}$$

Recursive WM filters are denoted as:

$<(A_N, \ldots A_1, B_0, B_1, \ldots B_M)>$

B. *Stability of Recursive WM Filters*

One of the main problems in the design of linear IIR filters is stability. In order to guarantee the BIBO stability of a linear IIR filter, the poles of its transfer function must lie within the unit circle in the complex plane. Unlike linear IIR filters, recursive WM filters are guaranteed to be stable. Recursive weighted median filters, are stable under the bounded-input bounded-output criterion, regardless of the values taken by the feedback coefficients $\{A_l\}$ for l = 1, 2… N.

C. *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. Lin and Huang 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. The proposed algorithm is simple and has less computation.

III. 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 methods are complex and has high computation. In case of median controlled algorithm, the selection of weights are 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 $|X_i - X'_i|$. Weight values can be obtained from the formula

$$\mathbf{a_i} = \mathbf{e}^{-\alpha|X_i - X'_i|} \quad \text{or}$$

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

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 $a=(a_1,a_2,a_3\ldots\ldots a_i)$ and the inputs $x=(X_1,X_2,X_3\ldots\ldots X_i)$ is given by

$\text{Weight Med}(X_1,X_2,X_3\ldots\ldots X_i) = \text{MED}\{(a_1 \lozenge X_1, a_2 \lozenge X_2, a_3 \lozenge X_3 \ldots\ldots a_i \lozenge X_i)$

where ◊ is the replication operator defined as

$a_i \lozenge X_i = (a_i, a_i \ldots\ldots a_i)$ 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 W,store the result in REFERENCE image.
2. Calculate the weight as
   Weight(i,j)= exp{- α|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.

IV. STRUCTURE OF THE FILTER

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

$$Y(n) = \text{MEDIAN}\left(|A1| \Diamond \text{sgn}(A1)Y(n-l)|^{N} \quad + \; |Bk| \Diamond \text{sgn}(X(n-k)|^{M2} \right)$$

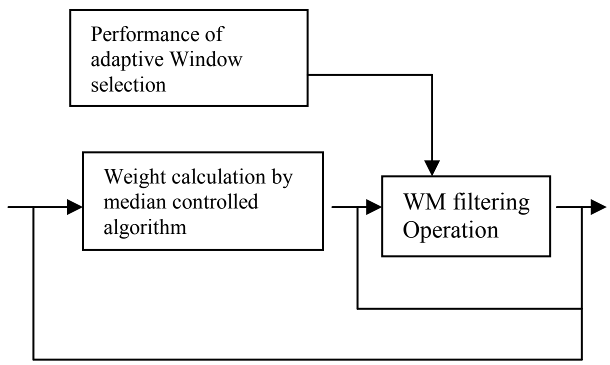


Fig1. Block diagram of Median controlled adaptive RWM filter

Let us consider the algorithm as stages.

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 ≤ 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 X N image
Moving window W,|W|=N=2k+1
Weight vector a=(a_1, a_2……..a_N)
Let Half Sum= $\sum^{N}_{i=1} a_i /2$
for i=1 to 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

V. RESULTS

The proposed ARWMF using median controlled algorithm is tested using the Lena, Zelda, parrot and flower color images. Fig2 &3 show the results Lena color image corrupted by 40% and 80% of noise densities. Fig 2&3 (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. Fig4 &5 show the results Zelda color image corrupted by 20% and 60% of noise densities and results of the different filters.. Tables I A,I B and I C shows the Comparison table of MSE, PSNR and MAE of different filters for Lena.jpg. And tables II A, II B and II C show the Comparison table of MSE, PSNR and MAE of different filters for Zelda.jpg. Fig 6(a, b, c, d, e & f) shows the results in graphical form. Fig 7 and 8 are the different filters output of parrot and flower color image at 30% and 90% of noise densities. Fig 9 show the comparison graph of the MAE and PSNR of different filters for color parrot and flower image.

TABLE I A
Comparison table of **MSE** of different filters for **Lena.jpg**

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

TABLE I B
Comparison table of **PSNR** of different filters for **Lena.jpg**

Noise density	SMF	WM	CWM	RWM	MC(lin's)	ARWMF
10	33.9	35.04	34.87	32.07	33.76	30.53
20	31.58	30.62	29.28	30.79	31.88	29.73
30	27.42	25.58	24.53	28.63	29.32	29.18
40	23.28	21.65	20.63	26.5	25.42	28.48
50	19.82	18.6	17.7	24.19	21.44	28.01
60	16.89	16.12	15.38	20.8	18.01	27.43
70	14.62	14.1	13.63	17.01	15.13	26.75
80	12.73	12.48	12.2	13.68	12.78	25.95
90	11.24	11.11	10.9	11.69	11.17	24.1

TABLE I C
Comparison table of **MSE** of different filters for **Lena.jpg**

Noise density	SMF	WM	CWM	RWM	MC(lin's)	ARWMF
10	1.44	1.12	0.92	1.39	0.82	2.19
20	1.71	1.49	1.43	1.66	1.2	2.34
30	2.31	2.43	2.55	2.46	1.73	2.49
40	3.63	4.22	4.8	3.53	2.73	2.87
50	6.5	7.15	8.26	4.66	4.83	2.98
60	10.18	11.56	13.22	7.08	8.7	3.13
70	15.86	17.42	19.011	11.95	15.04	3.41
80	22.42	24.58	25.97	21.66	23.9	3.89
90	32.09	32.9	33.69	31.25	33.29	4.93

Fig 2. (a) Original Lena 256 X256 image (b) Noisy image (density 40%) (c) SMF outputs (d) WMF output (e) RWM output (f) MC LIN's output (g) Proposed ARWMF output

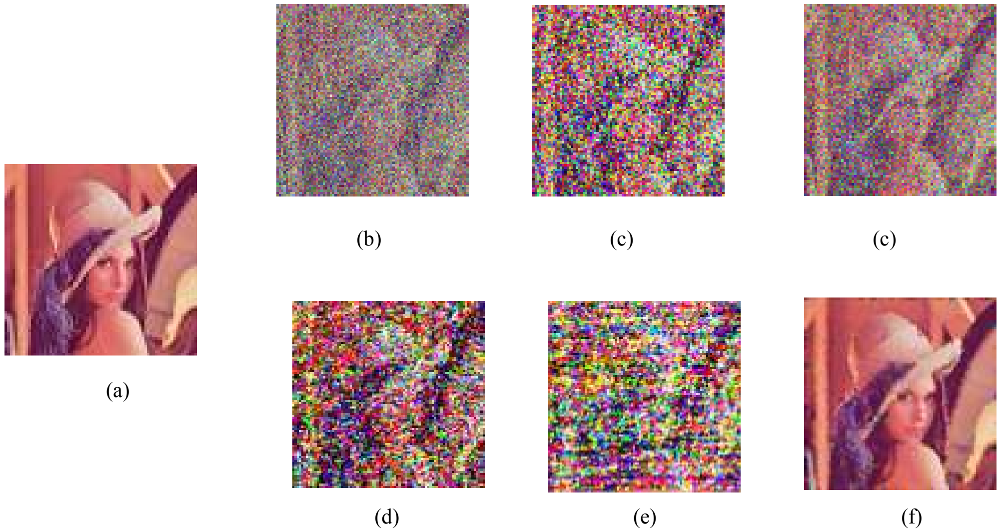


Fig 3. (a) Original Lena 256 X256 image (b) Noisy image (density 80%) (c) SMF outputs (d) WMF output (e) RWM output (f) MC LIN's output (g) Proposed ARWMF output

TABLE II A
Comparison table of **MSE** of different filters for **Zelda.jpg**

Noise density	SMF	WM	CWM	RWM	MC LINS	ARWMF
10	17.3889	14.2129	14.9769	26.7289	15.21	41.8609
20	36.1201	53.7289	66.7489	38.3161	27.04	50.6944
30	107.9521	167.1849	227.1049	36.6025	64	63.3616
40	294.1225	418.6116	552.7201	94.6729	161.29	66.0969
50	650.25	889.2324	1106.893	226.2016	424.7721	71.4025
60	1292.403	1558.67	1854.164	501.3121	967.8321	88.7364
70	2226.896	2597.941	2788.896	862.5969	1923.7	96.2361
80	3435.132	3659.04	3925.023	1858.472	3204.692	134.3281
90	4819.136	5026.81	5159.549	4352.041	4625.36	195.1609

TABLE II B
Comparison table of **PSNR** of different filters for **Zelda.jpg**

Noise density	SMF	WM	CWM	RWM	MC LINS	ARWMF
10	35.71	35.04	36.36	33.85	36.3	30.76
20	32.52	30.62	29.18	32.28	33.74	30.52
30	27.79	25.58	24.56	29.69	30.06	30.35
40	23.44	21.65	20.7	28.01	26.15	29.79
50	20	18.6	17.68	24.58	21.84	29.34
60	17.01	16.12	15.44	21.12	18.27	28.96
70	14.65	14.1	13.67	16.97	15.28	28.39
80	12.77	12.48	12.19	13.62	13.07	27.07
90	11.74	11.11	11	11.3	11	26.52

TABLE II C
Comparison table of **MAE** of different filters for **Zelda.jpg**

Noise density	SMF	WM	CWM	RWM	MC LINS	ARWMF
10	1.18	1	0.73	1.47	0.5	2.09
20	1.47	1.21	1.24	1.74	0.88	2.27
30	2.1	2.19	2.42	2.55	1.41	2.45
40	3.43	3.94	4.64	3.08	2.55	2.64
50	5.79	6.99	8.23	4.45	4.39	2.79
60	9.91	11.32	12.99	6.86	8.31	2.96
70	15.75	17.49	18.92	12.49	14.67	3.14
80	23.28	26.48	25.99	22.07	22.89	3.59
90	31.82	32.9	33.65	31.16	32.07	4.67

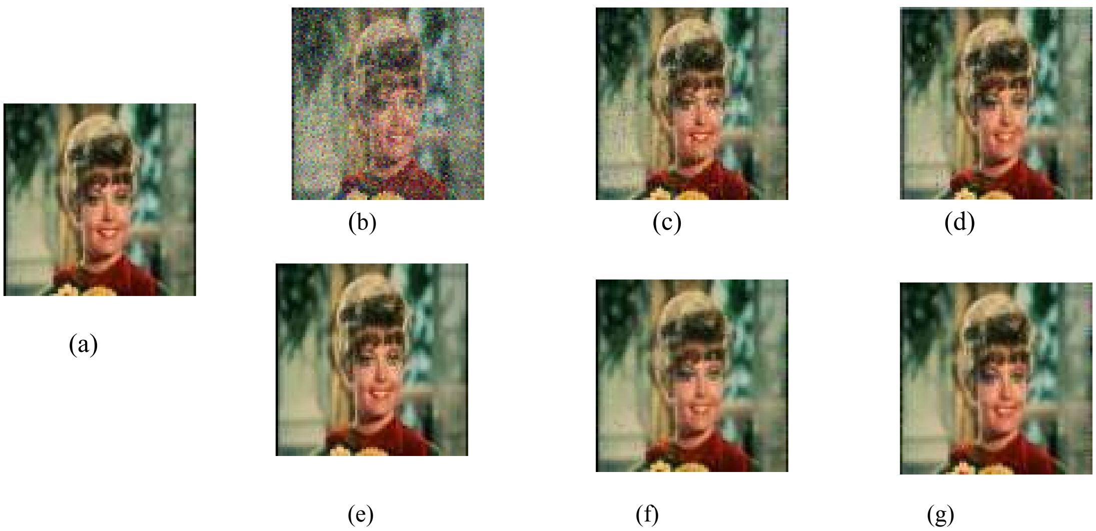
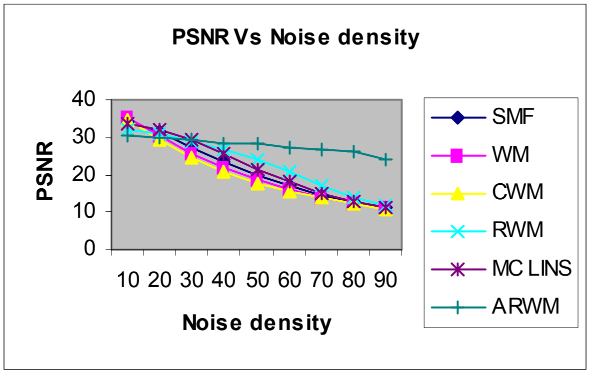
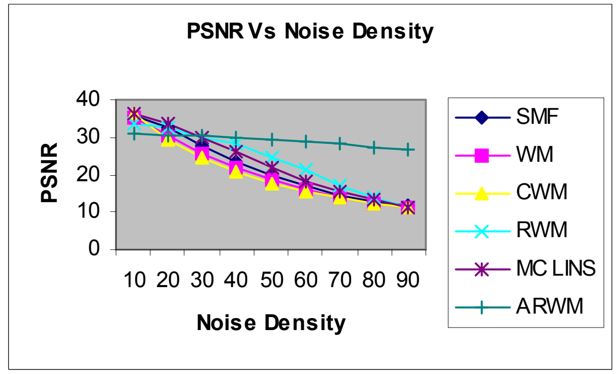


Fig 4. (a) Original Zelda 256 X 256 image (b) Noisy image (density 20%) (c) SMF outputs (d) WMF output (e) RWM output (f) MC LIN's output (g) Proposed ARWMF output

Fig 5. (a) Original Zelda 256 X 256 image (b) Noisy image (density 60%) (c) SMF outputs (d) WMF output (e) RWM output (f) MC LIN's output (g) Proposed ARWMF output



(a)



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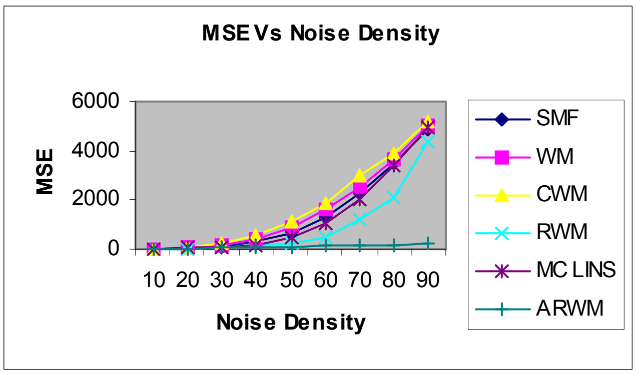

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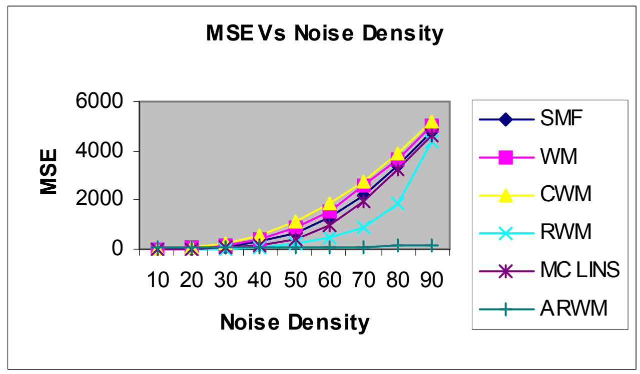
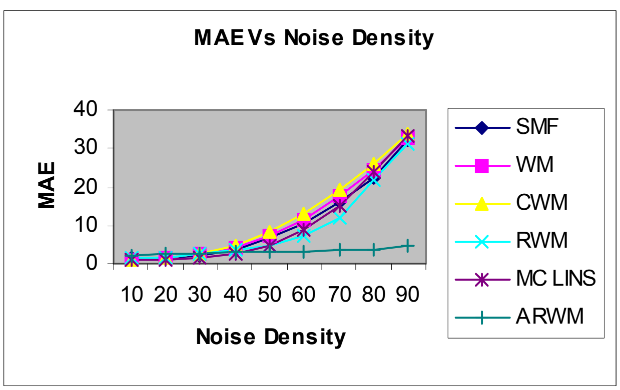


(d)



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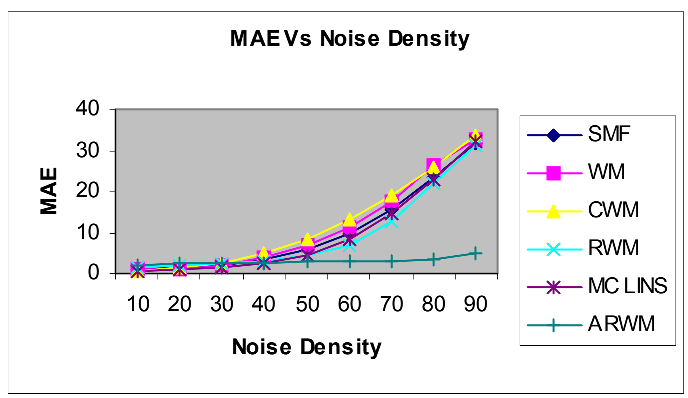


(f)

Fig 6. (a) & (b) Comparison graph of PSNR at different noise density of Lena & Zelda image,
(c) & (d) Comparison graph of MSE at different noise density of Lena & Zelda image,
(e) & (f) Comparison graph of MAE at different noise density of Lena & Zelda image.

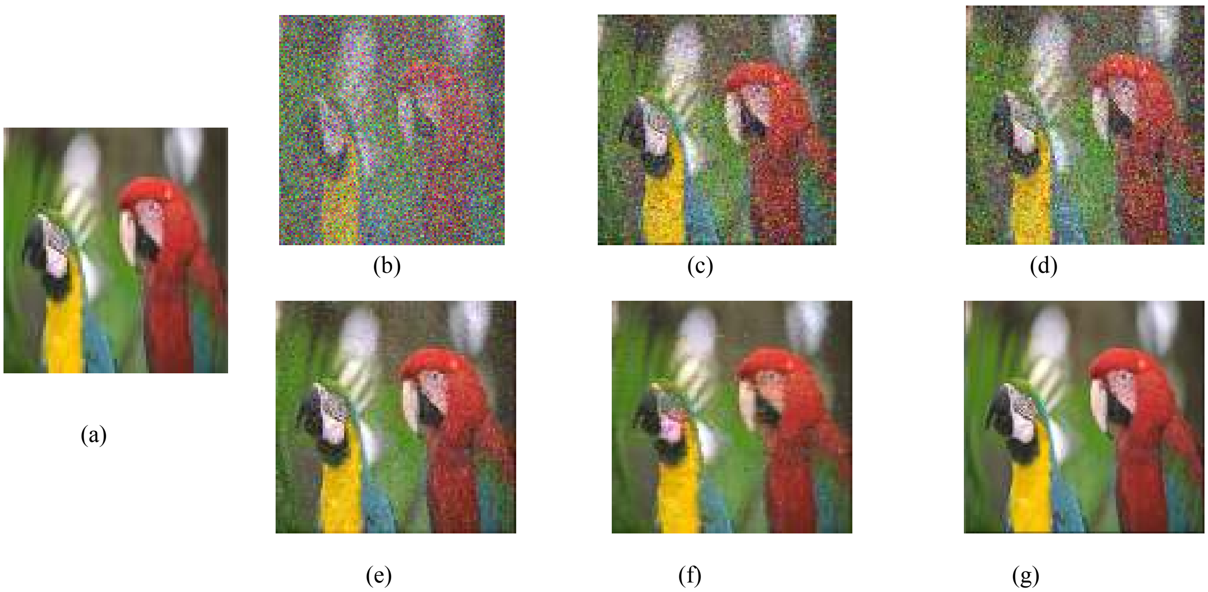


Fig 7. (a) Original Parrot 512 X 512 image (b) Noisy image (density 30%) (c) SMF outputs (d) WMF output (e) RWM output (f) MC LIN's output (g)Proposed ARWMF output

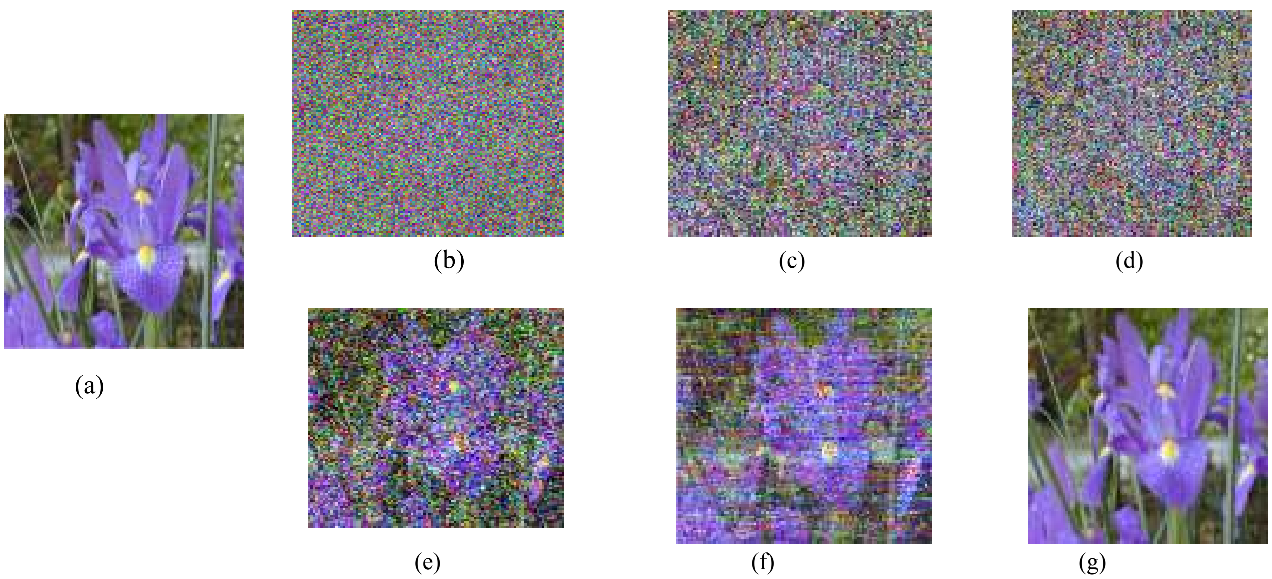
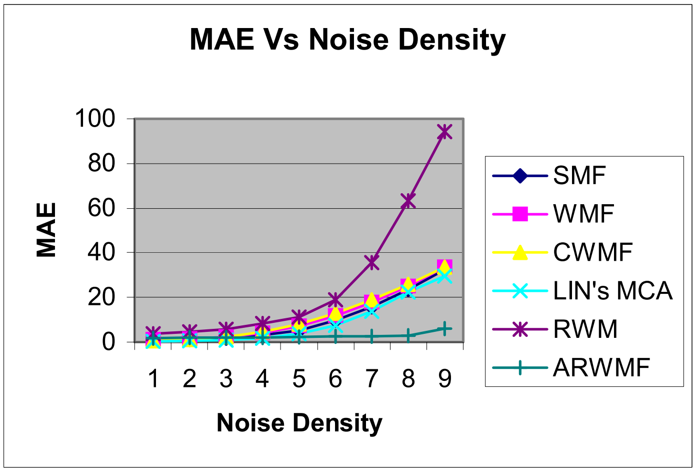
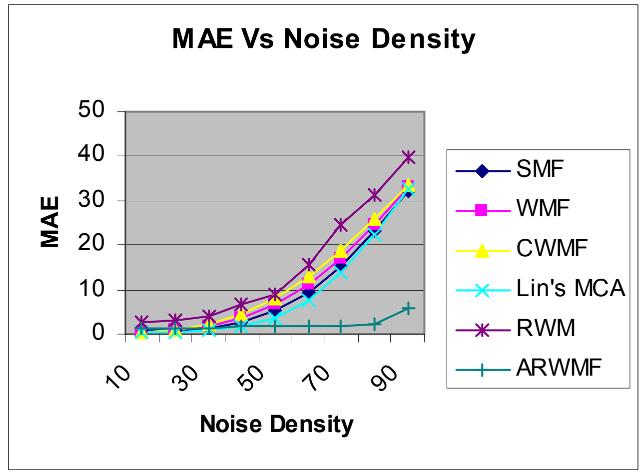


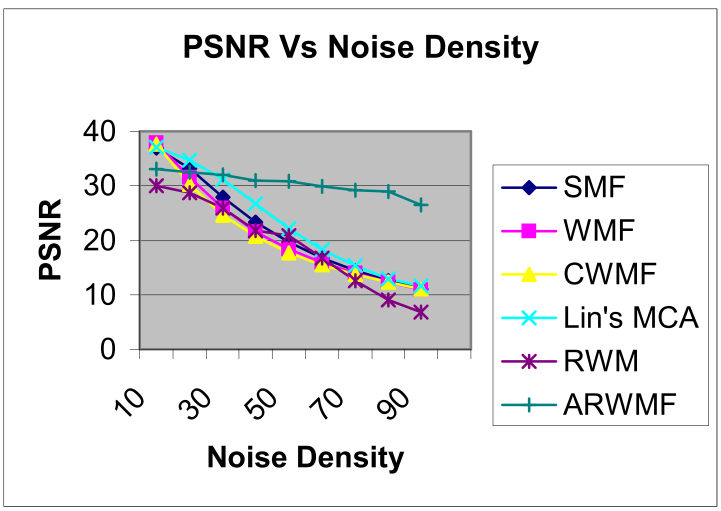
Fig 8. (a) Original Flower 512 X 512 image (b) Noisy image (density 90%) (c) SMF outputs (d) WMF output (e) RWM output (f) MC LIN's output (g) Proposed ARWMF output



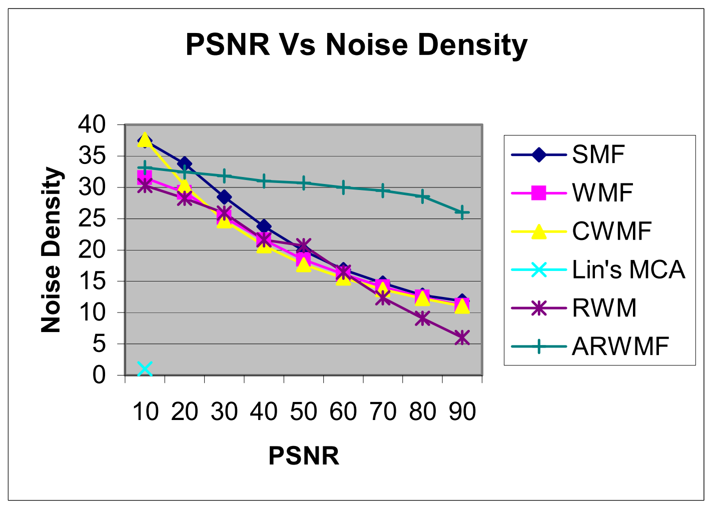
(a)



(b)



(c)



(d)

Fig 9. (a) & (b) Comparison graph of MAE at different noise density of Parrot & Flower image ,
(c) & (d) Comparison graph of PSNR at different noise density of Parrot & Flower image

VI. Conclusion

Generally, the RWM filters are designed only for the fixed window length which causes blurring in the output samples. 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, the proposed filter is designed where the window length is determined by the width of the impulsive noise presented in the input sample. Therefore there is no chance of filtering the uncorrupted pixel which reduces the blurring in the output sample. The weights calculated by using the median controlled algorithm is producing very effective result and preserve fine details and edges. The MSE is also very less when compared to other median type algorithms.

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