Efficient Algorithm for Enhancement of Images Corrupted by Salt & Pepper Noise

SHYAM LAL[*] AND MAHESH CHANDRA[**]
[*]Research Scholar, ECE Department, Birla Institute of Technology, Mesra, Ranchi (JH.), INDIA
[**]ECE Department, Birla Institute of Technology, Mesra, Ranchi (JH.), INDIA
[shyam_rao24@rediffmail.com, shrotriya69@rediffmail.com]

Abstract:- In this paper an efficient algorithm is proposed for removal of salt & pepper noise from digital images. The proposed algorithm consists of two stages: in first stage the noisy image is processed by adaptive median filter and in the second stage the output of first stage is further processed by modified mean filter. The first stage classifies noisy pixels by comparing each pixel in the image to its surrounding neighbourhood pixels. If the pixel is different from a majority of its neighbours, then it is considered as one of the noisy pixels. Noisy pixels are replaced by the median value of the neighbourhood pixels. Second stage works in two phases: in the first phase the noisy pixels are detected and in second phase each noisy pixel are replaced by the mean value of noise free pixel of 2×2 window. Simulation and experimental results show that the proposed algorithm consistently works well in suppressing the salt and pepper noise density (up to 95%). The proposed Adaptive Median based modified Mean filter (AMMF) outperforms a number of other existing filters such as standard median filter (SMF), centre weighted median filter (CWMF), progressive switching median filter (PSMF), open-close sequence filter (OCSF), decision based algorithm (DBA), modified decision based unsymmetric trimmed median filter (MDBUTMF) for noise removal in terms of high PSNR, low MSE and reduced streaking effect. The proposed algorithm is suitable for low level noise density as well as high level noise density. The proposed algorithm demonstrates better performance as compared to other existing techniques on different gray scale images.

Key-words- Median filter, Centre weighted median filter, Open-close sequence filter, Decision based algorithm, Modified decision based unsymmetric trimmed median filter.

1 Introduction

The transmission and acquisition of digital images through sensors or communication channels are often interfered by impulse noise. It is important to eliminate the impulse noise from the image before some subsequent processing such as edge detection, object reorganization and image segmentation. During last decade a number of algorithms have been proposed for removal of impulse noise. The salt and pepper noise is a special type of impulsive noise in which some portion of image pixel values are replaced by either minimum or maximum values. The main goal of salt & pepper noise removal is that it removes the noise from the image while preserving the other image details. The linear filters used for impulse noise removal work much better for low noise level density than to high noise level density. For high noise level density, the output images are blurred and edges are not preserved accurately by the linear filters. Therefore the non linear filters have been used for improved filtering performance in terms of impulse noise removal and preservation of other details of the images. In this context various non linear filters have been proposed by various researchers for removal of salt & pepper noise.

Since last decade, median based filters have attracted much attention due to their simplicity and information preservation capabilities [1-5]. The main drawback of the median filter is that it also modifies non noisy pixels thus removing some fine details of the image. Therefore it is only suitable for very low level noise density [6]. At high noise density it shows the blurring for the larger template sizes and it is not able to suppress the noise completely for smaller template sizes. Therefore, contemporary switching based filters split the image denoising process in two steps. The first step is the detection of noise and second step is the replacement of the noisy pixels value with estimated value, where the median is commonly used as an estimator. These are weighted median filter [6-7], adaptive impulse detection using centre weighted median filter [8], rank order filtering algorithm [9-10]. The performance of the centre weighted median filter (CWMF), standard adaptive median filter (AMF) and progressive switching median filter (PSMF) are good at the lower noise density level due to less numbers of the noisy pixels which are replaced with the median values [11-12]. At higher noise density, there are a large number of the noisy pixels which need to be replaced. Therefore the size of the template needs to be increased for improvement of the results. After that, all the noisy pixels are replaced with median value pixel which results in loss of information. Predefined threshold is the main drawback of the switching median filter [13] and decision based filter due to that some details and edges are also removed in case of high density salt and pepper noise. Ideally the filtering should be applied only to the values of the noisy pixel while keeping the values of the noise free pixels. To overcome the disadvantages of the mentioned filtering techniques a two stage algorithm has been proposed [14]. In this algorithm adaptive median filter is used in first stage to classify the values of the noisy and noise free pixels. In second stage regularization technique is used for noisy pixels to preserve the details and edges as much as possible. Due to large template size in both stages, processing time is too large and more complexity is involved in its implementation. To avoid this drawback, open close sequence filter [15] has been proposed. This algorithm is based on mathematical morphology, which is suitable only in high density impulse noise (noise density ranging from 45% to 80%). The main drawback of this algorithm is that its performance deteriorates in both low noise density and very high noise density. In order to overcome this drawback, decision based algorithm (DBA) is proposed [16]. In this algorithm, image is denoised by using a 3X3 window. If the processing pixel value is '0' or '255', it is processed otherwise left unchanged. At high noise density the median value will be '0' or '255' which is noisy. In such case, neighbouring pixel is used for replacement. This repeated replacement of neighbouring pixel produces streaking effect [17]. In order to avoid this drawback, decision based unsymmetric trimmed median filter (DBUTMF) is proposed [18]. At high noise densities, if the selected window contains all 0's or 255's or both then, trimmed median value cannot be obtained. To avoid the major drawback of decision based unsymmetric trimmed median filter, modified decision based unsymmetric trimmed median filter is proposed [19]. In this algorithm the noisy image is denoised by using 3X3 window elements and then pixels are arranged in increasing or decreasing order. Then the pixel values '0's and '255's in the image (i.e., the pixel values responsible for the salt and pepper noise) are removed from the image. Then the median value of the remaining pixels is taken. This median value is used to replace the noisy pixel. This algorithm does not give better results at high noise density ranging from 70% to 95%. So to overcome the drawback of modified decision based unsymmetric trimmed median filter (MDBUTMF) algorithm [19], a new & efficient algorithm is proposed which is suitable for elimination of high density impulse noise ranging from 60% to 95%. The proposed AMMF algorithm consists of two stage : in fist stage the noisy image is processed by adaptive median filter and in the second stage the output of first stage is further processed by modified mean filter.

The rest of the paper is organized as follows. The proposed AMMF algorithm is described in section 2, where its implementation steps are also discussed. Section 3 reports a number of simulation and experimental results to demonstrate the performance of the proposed algorithm. Finally, conclusion is drawn in section 4.

2 Proposed AMMF Algorithm

The proposed AMMF algorithm consists of two stages, in first stage the noisy image is processed by adaptive median filter [12]. In second stage the output of first stage is further processed by modified mean filter if the image is corrupted by high density salt & paper noise. The first stage classifies pixels as noise by comparing each pixel to its neighbourhood pixels. The size of the neighbourhood is adjustable. A pixel is considered noisy when it is different from majority of its neighbourhood pixels. These noisy pixels are replaced by the median value of neighbourhood pixels. Further the second stage also works in two steps: in the first step the noisy pixels are detected and in the second step each noisy pixel are replaced by the mean of noise free pixel of 2×2 window.

2.1 Noise Detection in Modified Mean filter

In this section the main purpose is to identify the "noisy pixel" and "noise free pixels". It is described as follows:

Based on [1] and [14], we assume that the two intensities that present the impulse noise are the maximum and the minimum values of the image's dynamic range (i.e. 0 and L-1). Thus, in this stage, at each pixel location (x, y) ,we mark the mask α by using the equation (1)

$$\alpha(x,y) = \begin{cases} 1 & for\ g(x,y) = L-1 \\ 1 & for\ g(x,y) = 0 \\ 0 & otherwise \end{cases} \tag{1}$$

Where the value '1' indicates noisy pixel and the value '0' indicates the noise free pixel

2.2 Implementation of AMMF Algorithm

The proposed algorithm involves the following steps to remove the impulse noise:

Stage-I:

Step(1).Initialize the window size (maximum value of window size is 13X13) of the filter.

Step(2).Check if centre pixel is noisy in selected window, if YES then go to step 3. Otherwise move centre of window to next pixel and redo step 2.

Step(3).Find the value of Z_{min}, Z_{max} and Z_{med} in the selected window.

Step(4).Determine if Z_{med} is noisy by $Z_{min} < Z_{med} < Z_{max}$. If it holds, Z_{med} is noise free pixel and jump to step 6. Otherwise, Z_{med} is noisy and go to step 5.

Step(5).Increase window size and go back to Step 3.

Step(6).Replace the centre pixel with Z_{med}.

Step(7).Reset window size and move the centre of window to next pixel.

Step(8).Repeat the steps until all pixels are processed.

At high noise density of salt and paper noise, some of pixels are still noisy in stage-I which are further removed by passing through the entire image by stage II algorithm.

Stage-II:

Step(i). Initialize the window size of the filter by 2×2 window.

Step(ii). Find out the noise free pixels present in 2×2 window.

Step(iii). Find out the mean value of the noise free pixels in selected window.

Step(iv). Replace the noisy pixel by the calculated mean value in step (iii).

Step(v). Repeat steps from (i)- (iv) to process the entire image for removal of Salt & Pepper Noise.

3 Simulation & Experimental Results

In order to demonstrate the performance of AMMF algorithm, it is tested on different gray scale natural images (i.e. 8-bit/pixel) with the noise density (N.D.) ranging from 10% to 95%. The AMMF algorithm gives better result as compared to standard median filter (SMF), centre weighted median filter (CWMF), progressive switching median filter (PSMF), open-close sequence filter (OCSF), decision based algorithm (DBA), modified decision based unsymmetric trimmed median filter (MDBUTMF). Each time the test image is corrupted by salt & pepper noise of different noise densities ranging from 10% to 95%. The performance of AMMF algorithm is expressed in terms of the peak signal to noise ratio (PSNR) and mean squared error (MSE).The PSNR estimates the quality of a reconstructed image with respect to an original image. Reconstructed images with higher PSNR are better. PSNR is defined in dB in equation (2).

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

Where MSE is mean squared error between original image (x) and denoised image ($\hat{x}$) which is given by equation (3)

$$MSE = \frac{1}{N_1 \times N_2}\sum_{i=1}^{N_1}\sum_{j=1}^{N_2}\left(x(i,j) - \hat{x}(i,j)\right)^2 \tag{3}$$

3.1 Experiment 1

Table 1 and Table 2 demonstrate the comparison of PSNR and MSE values of different filters respectively for gray scale House & Lena images with noise density (N.D.) ranging from 10% to 95%. The performance of AMMF algorithm is compared with various existing techniques such as standard median filter (SMF), progressive switching median filter (PSMF), centre weighted median filter (CWMF), open-close sequence filter (OCSF), decision based algorithm (DBA), modified decision based unsymmetric trimmed median filter (MDBUTMF). It can be noticed from Table1 and Table 2 that AMMF algorithm, gives better result in comparison to other existing techniques in terms of PSNR & MSE for low level noise density as well as high level noise density. Fig. 1 and Fig. 2 illustrate the graphical comparison of PSNR performance metric for different denoising algorithms for House & Lena image respectively. Fig. 3 and Fig. 4 illustrate the graphical comparison of MSE performance metric for different denoising algorithms for House & Lena images respectively.

3.2 Experiment 2

In order to demonstrate visual enhancement of AMMF algorithm, another experiment is conducted on Lena & House images with noise density (N.D.) ranging from 80% to 95%. The visual enhancement of AMMF algorithm is compared with various existing techniques such as standard median filter (SMF), progressive switching median filter (PSMF), centre weighted median filter (CWMF), open-close sequence filter (OCSF), decision based algorithm (DBA), modified decision based unsymmetric trimmed median filter (MDBUTMF). The visual enhancement of House & Lena images are shown in Fig. 5(B), 5(C), 5(D), 5(E), 5(F), 5(G), 5(H), 6(B), 6(C), 6(D), 6(E), 6(F), 6(G), 6(H), Fig. 7(B),7(C), 7(D), 7(E), 7(F),7(G), 7(H), Fig. 8(B), 8(C), 8(D), 8(E), 8(F), 8(G), 8(H), Fig. 9(B), 9(C), 9(D), 9(E), 9(F), 9(G), 9(H) and Fig. 10(B), 10(C), 10(D), 10(E), 10(F), 10(G), 10(H) with noise density (N.D.) i.e. 0.80, 0.90 and 0.95 respectively. It is clear from Fig. 5 to Fig.10 that the image recovered from the AMMF algorithm is better than other noise removal algorithms in terms of visibility.

Table 1: Comparative PSNR (dB) of different filters for Gray scale Image

Algorithm / image		SMF	PSMF	CWMF	OCSF	DBA	MDBUTMF	AMMF
House	ND=10%	36.16	39.13	35.14	34.87	35.85	38.12	**45.84**
	ND=20%	30.26	33.22	31.44	33.98	33.20	35.10	**41.67**
	ND=30%	24.10	28.95	28.28	33.10	30.98	33.22	**39.10**
	ND=40%	19.19	25.38	24.55	31.73	29.42	31.61	**36.88**
	ND=50%	15.38	15.33	20.91	30.38	27.93	29.96	**34.75**
	ND=60%	12.38	12.36	17.61	28.69	26.93	28.17	**33.00**
	ND=70%	10.04	10.04	14.16	26.62	24.98	26.25	**30.78**
	ND=80%	8.15	8.11	11.23	24.31	22.73	24.26	**28.14**
	ND=90%	6.66	6.61	8.73	20.93	20.15	21.25	**25.88**
	ND=95%	6.01	6.03	7.69	18.56	17.67	18.98	**24.69**
Lena	ND=10%	33.25	36.82	32.42	29.60	35.62	37.95	**38.09**
	ND=20%	28.91	32.40	29.61	29.22	32.24	34.73	**35.91**
	ND=30%	23.63	28.94	27.18	28.62	30.02	32.39	**33.69**
	ND=40%	18.98	24.97	23.81	27.78	28.51	30.27	**31.90**
	ND=50%	15.29	20.48	20.43	26.76	26.99	28.19	**30.28**
	ND=60%	12.36	12.26	17.07	25.50	25.36	26.56	**28.68**
	ND=70%	9.97	9.95	13.96	24.03	22.83	24.13	**26.97**
	ND=80%	8.17	8.09	11.15	21.55	21.04	21.73	**24.89**
	ND=90%	6.68	6.65	8.72	18.30	18.11	18.62	**23.04**
	ND=95%	5.98	5.99	7.64	16.22	16.56	17.22	**21.88**

Table 2: Comparative MSE of different filters for Gray scale image

Algorithm / image		SMF	PSMF	CWMF	OCS	DBA	MDBUTMF	AMMF
House	ND=10%	15.75	7.94	19.91	21.20	16.16	10.02	**1.69**
	ND=20%	61.19	30.97	46.67	26.03	31.14	20.09	**4.43**
	ND=30%	253.01	82.81	96.71	31.83	51.85	30.97	**7.99**
	ND=40%	784.17	188.59	227.87	43.71	74.40	44.88	**13.34**
	ND=50%	1883.95	1906.15	526.91	59.61	104.79	65.62	**21.79**
	ND=60%	3757.68	3780.01	1126.51	87.96	132.00	99.10	**32.62**
	ND=70%	6443.06	6449.16	2497.44	141.63	206.73	154.19	**54.28**
	ND=80%	9950.40	10051.84	4915.19	240.89	346.64	243.82	**99.84**
	ND=90%	14043.89	14186.02	8717.05	524.32	627.59	487.61	**167.85**
	ND=95%	16305.99	16203.03	11069.30	904.86	1111.57	822.39	**220.73**
Lena	ND=10%	30.78	13.53	37.21	71.24	17.82	10.42	**10.09**
	ND=20%	83.49	37.46	71.13	77.90	38.82	21.88	**16.68**
	ND=30%	281.91	83.07	124.20	89.25	62.09	37.50	**27.79**
	ND=40%	822.30	206.84	270.32	108.40	91.63	61.10	**41.95**
	ND=50%	1925.19	582.64	588.05	137.09	130.04	98.64	**60.99**
	ND=60%	3774.38	3860.23	1270.0	183.22	189.26	143.57	**88.19**
	ND=70%	6545.43	6577.23	2610.23	257.36	338.90	251.23	**130.59**
	ND=80%	9902.36	10088.95	4930.12	454.67	511.77	436.59	**210.66**
	ND=90%	13962.06	14068.25	8720.21	962.27	1004.81	893.47	**322.98**
	ND=95%	16412.70	16374.33	11196.45	1552.25	1435.75	1233.34	**421.81**

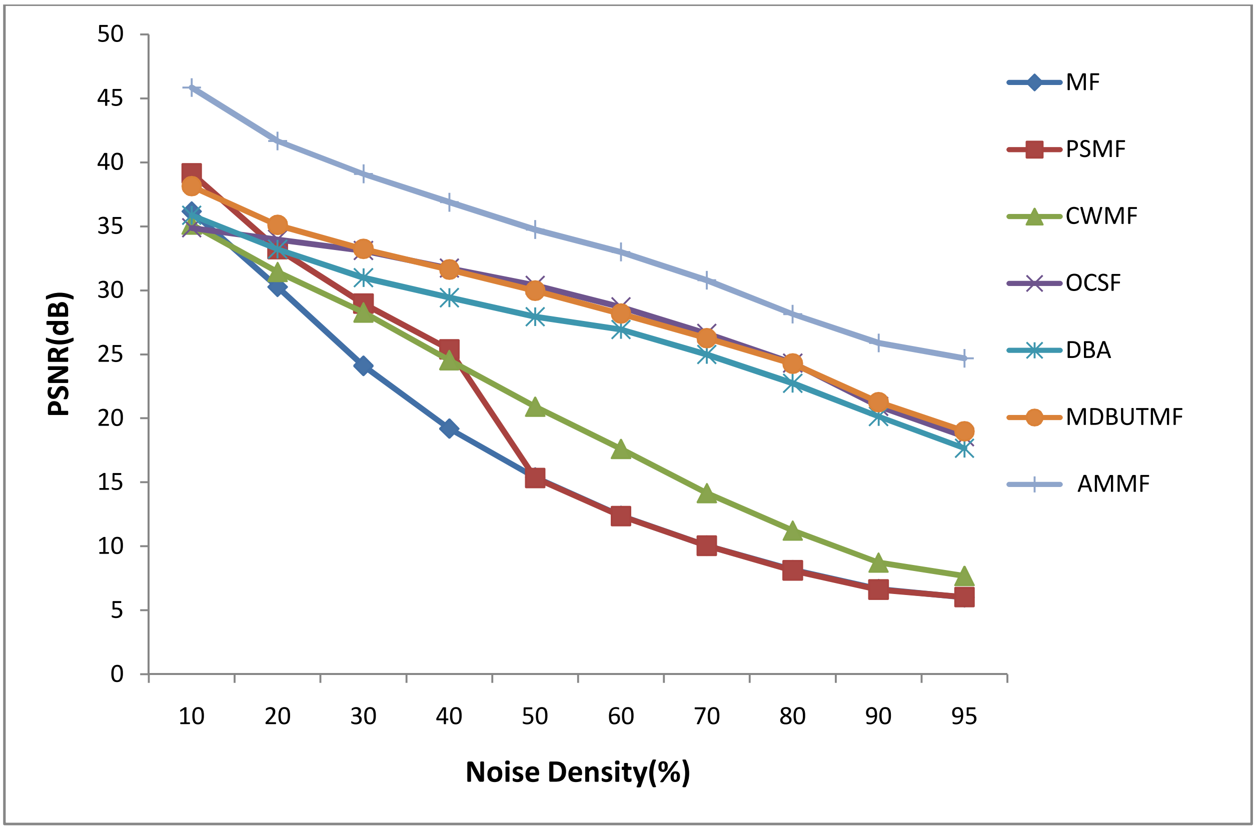

Fig.1. PSNR vs. Noise Density for House Image

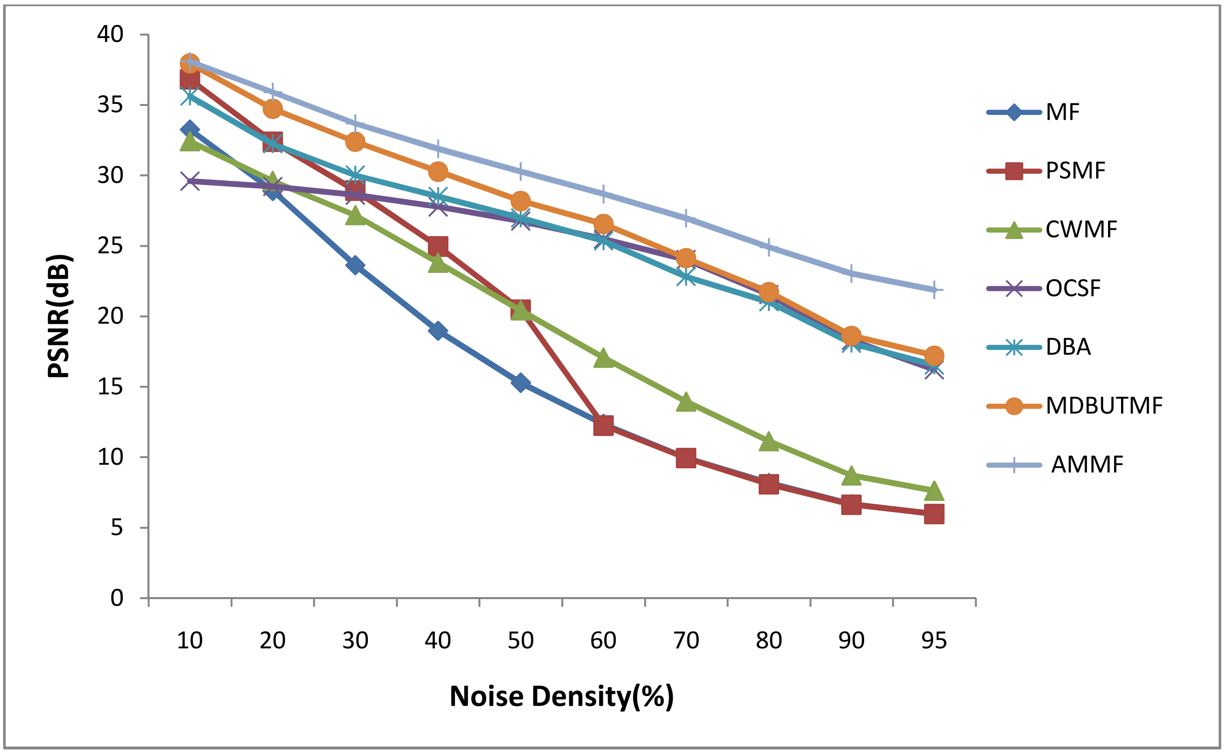

Fig.2. PSNR vs. Noise Density for Lena Image

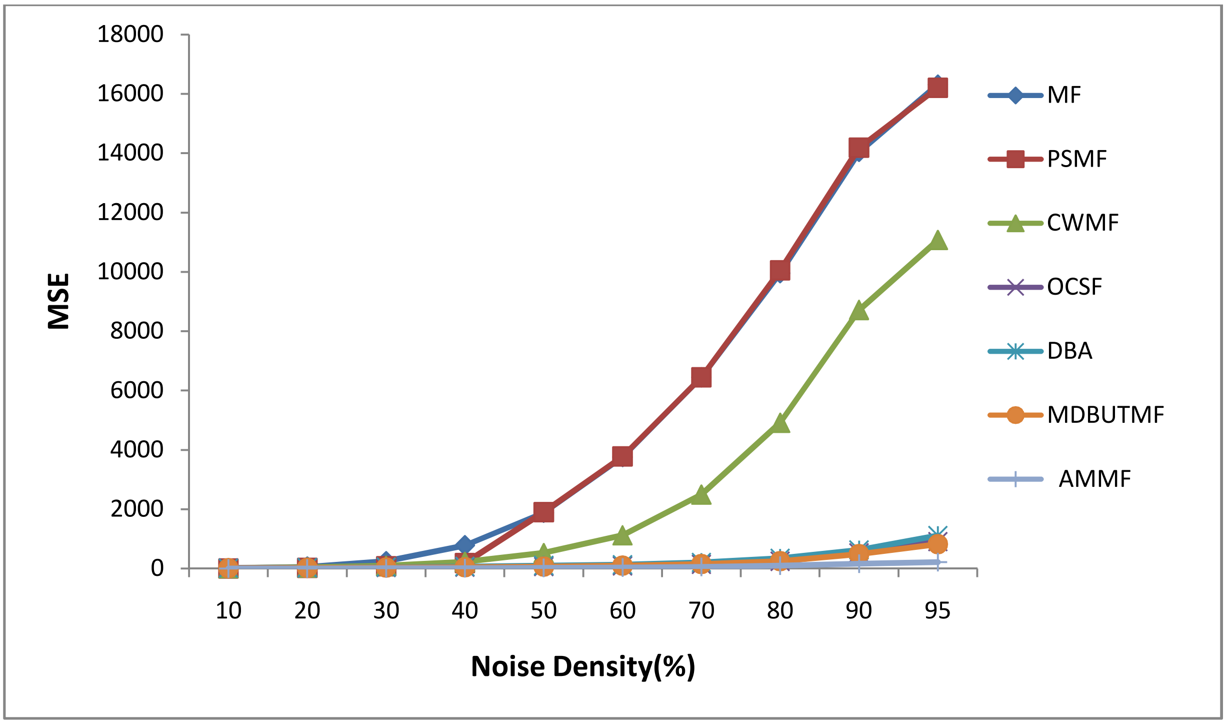

Fig.3. MSE vs. Noise Density for House Image

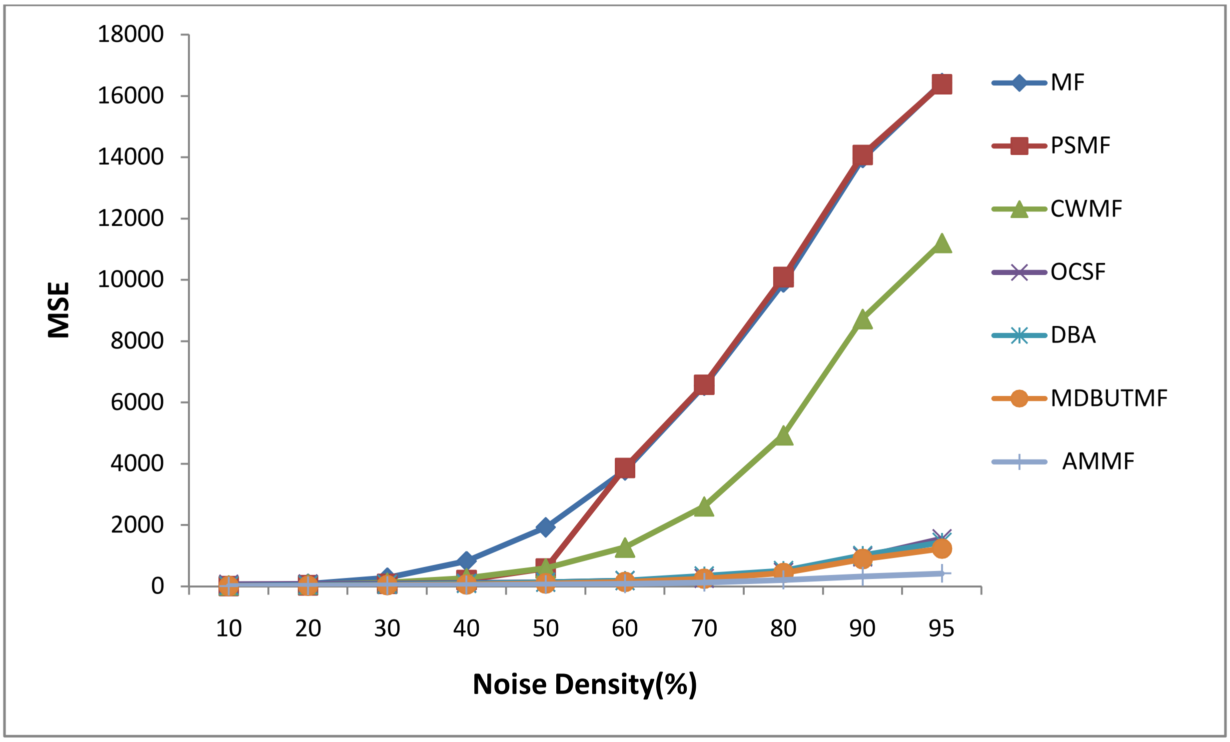

Fig.4. PSNR vs. Noise Density for Lena Image

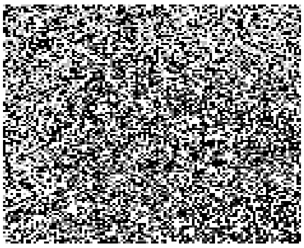

Fig. 5(A). Noisy image with noise density 80%

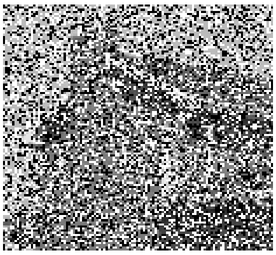

Fig. 5(B). Output of SMF

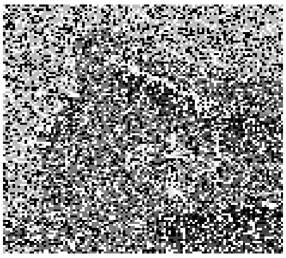

Fig.5(C). Output of PSMF

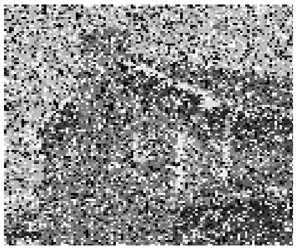

Fig. 5(D). Output of CWMF

Fig.5(E).Output of OCSF

Fig. 5(F). Output of DBA

Fig. 5(G). Output of MDBUTMF

Fig. 5(H). Output of AMMF

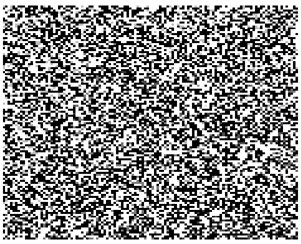

Fig. 6(A). Noisy image with noise density 90%

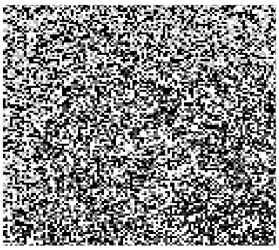

Fig. 6(B). Output of SMF

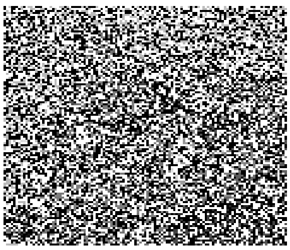

Fig.6(C). Output of PSMF

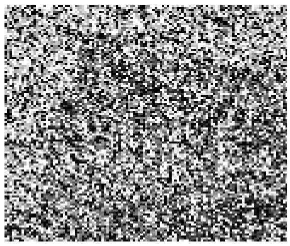

Fig.6(D). Output of CWMF

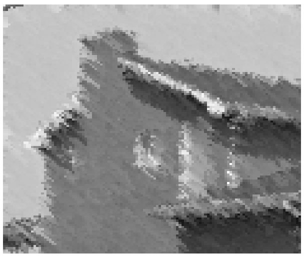
Fig.6(E).Output of OCSF


Fig. 6(F). Output of DBA


Fig. 6(G). Output of MDBUTMF


Fig. 6(H). Output of AMMF

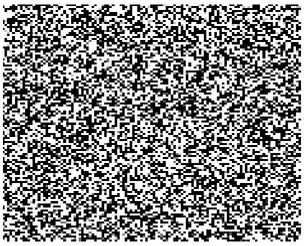
Fig. 7(A). Noisy image with noise density 95%

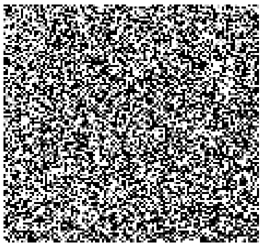
Fig. 7(B). Output of SMF

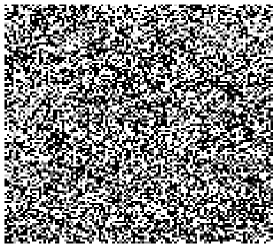
Fig.7(C). Output of PSMF

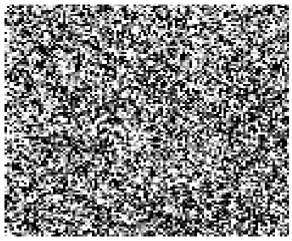
Fig. 7(D). Output of CWMF

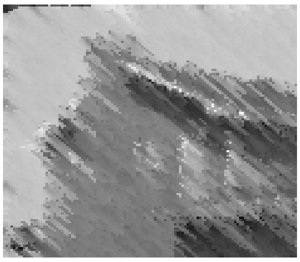
Fig.7(E).Output of OCSF

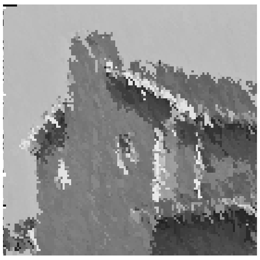
Fig. 7(F). Output of DBA


Fig. 7(G). Output of MDBUTMF


Fig. 7(H). Output of AMMF


Fig.8(A)Noisy image with noise density 80%

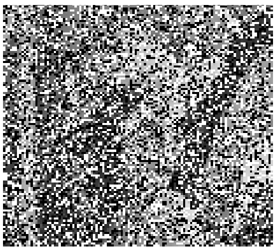
Fig. 8(B). Output of SMF

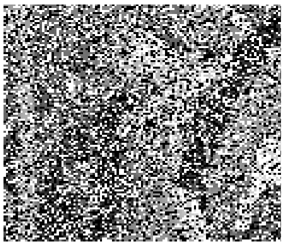
Fig.8(C). Output of PSMF

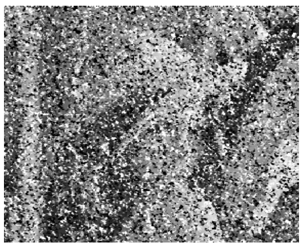
Fig. 8(D). Output of CWMF


Fig. 8(E). Output of OCSF


Fig. 8(F). Output of DBA

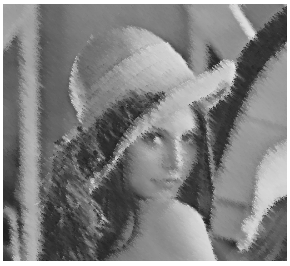
Fig. 8(G). Output of MDBUTMF


Fig. 8(H). Output of AMMF

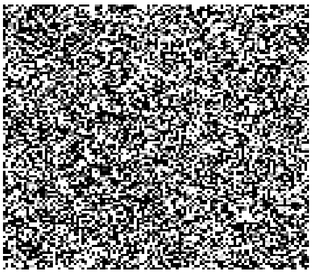
Fig. 9(A). Noisy image with noise density 90%

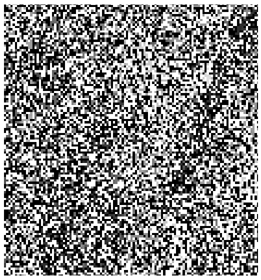
Fig. 9(B). Output of SMF

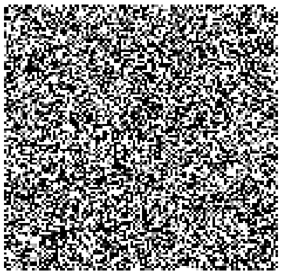
Fig.9(C). Output of PSMF

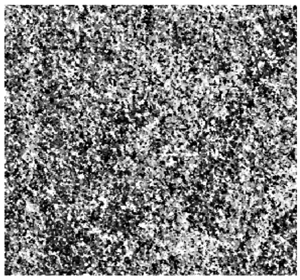
Fig. 9(D). Output of CWMF

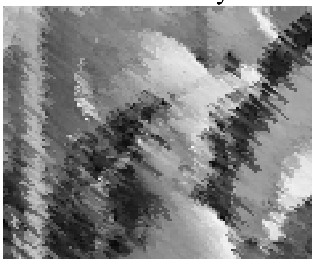
Fig.9(E).Output of OCSF


Fig. 9(F). Output of DBA


Fig. 9(G). Output of MDBUTMF


Fig. 9(H). Output of AMMF

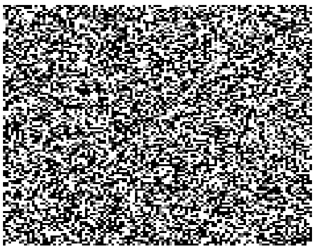
Fig. 10(A). Noisy image with noise density 95%

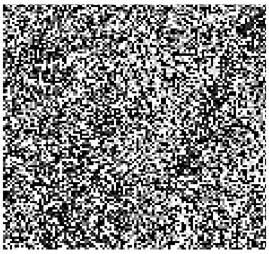
Fig. 10(B). Output of SMF

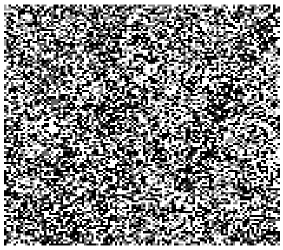
Fig.10(C). Output of PSMF

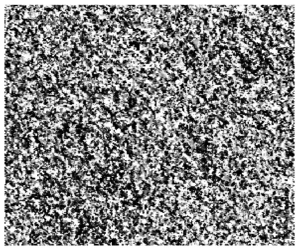
Fig. 10(D). Output of CWMF

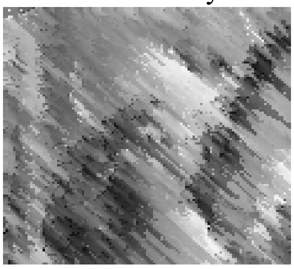
Fig.10(E).Output of OCSF

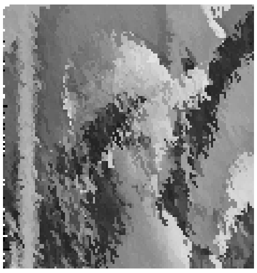
Fig.10 (F). Output of DBA

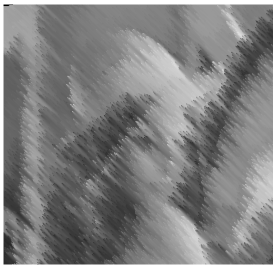
Fig. 10(G). Output of MDBUTMF


Fig.10 (H). Output of AMMF

4. Conclusion

This paper proposed a new algorithm (AMMF) for removal of salt & pepper noise from digital images. The AMMF algorithm has been tested on different gray scale natural images with noise density ranging from 10% to 95%. The performance of AMMF algorithm has been evaluated and compared in terms of PSNR and MSE values. The performance of AMMF algorithm has been compared with various existing techniques such as standard median filter (MF), progressive switching median filter (PSMF), centre weighted median filter (CWMF), open-close sequence filter (OCSF), decision based algorithm (DBA), modified decision based unsymmetric trimmed median filter (MDBUTMF). Both visual and quantitative results are demonstrated. The AMMF algorithm demonstrated well in low level noise density as well as high level noise density. Even at 95% noise density levels the proposed algorithm provided better results in comparison with other existing algorithms.

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