Removal of High Density Salt & Pepper Noise Through Super Mean Filter for Natural Images

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Abstract

A super-mean filter (SUMF) is proposed to remove high density salt & pepper noise from digital images. The proposed filter works in two stages, in the first stage the noisy pixels are detected and in the second stage each noisy pixel is replaced by the mean value of noise free pixel of 2×2 matrix. Extensive simulation and experimental results shows that the proposed filter works well consistently for suppressing the salt & pepper noise. The performance of proposed filter is compared with the other existing filters, 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). The proposed filter shows better performance as compared to above mentioned filters for noise removal from different gray scale images.

Keywords: *Super mean filter, 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, image segmentation and object reorganization. During last one decade various algorithms have been proposed for removal of impulse noise. The salt & pepper noise is a special type of impulse noise in which some portion of image pixel values are replaced by either minimum or maximum pixel values. The main objective of salt & pepper noise removal is that it removes the noise from the image by preserving the other image details. The linear filters used for impulse noise removal works much better for low noise density as compared to high noise density. For high noise density, the output images are blurred and edges are not preserved accurately by the linear filters. Therefore the non- linear filters have been used to provide better 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 removing salt & pepper noise.

During last one decade, median based filters have attracted very 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. At high noise density it shows the blurring for the larger template sizes and not able to suppress the noise completely for smaller template sizes. Therefore, contemporary switching filters split the denoising process in two steps. First one is detection of noise and second one is the replacement of the noisy pixel value with estimated median value. These are weighted median filter [6-7], adaptive impulse detection using centre weighted median [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) algorithms are good at the lower noise density due to less numbers of the noisy pixels which are replaced with the median values [11-12]. But at high noise density, there are a large number of the noisy pixels which are need to be replaced, therefore the size of the template will be larger to provide the better performance; however, the values of the noisy pixel and its replacement as median values are less correlated which results in information loss. The main disadvantage of the switching median filter [13] and decision based filter is that it is based on the predefined threshold, due to this some details and edges are also removed particularly in case of high noise density. Ideally the filtering should be applied only to the values of the noisy pixel while keeping the values of the noise free pixels. In order to overcome the disadvantages of these mentioned filtering techniques a two stage algorithm has been proposed [14]. In this algorithm an adaptive median filter is used in first stage to classify the values of the noisy and noise free pixels and detail preserving regularization technique is used in second stage to preserve the details and edges as much as possible. Due to large template size, processing time is too large and more complexity is involved in its implementation. In order to avoid this drawback, open-close sequence filter (OCSF) has been proposed [15]. This algorithm is based on mathematical morphology, which is suitable only for high density impulse noise (noise density ranging from 50% to 80%). The main drawback of this algorithm is that its performance is not good in very low noise density as well as in very high noise density. To overcome this drawback, decision based algorithm (DBA) is proposed [16]. In this algorithm, image is denoised by using a 3X3 window. The image is denoised for pixel value '0' or '255' else it is 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 (MDBUTMF) is proposed [19]. In this filter the noisy image is denoised by using 3X3 window elements which 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 & 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%. Therefore to avoid the drawback of modified decision based unsymmetric trimmed median filter, a new & efficient algorithm is proposed in this paper. This is suitable for elimination of high density impulse noise ranging from 60% to 95%. In this filter the values of the noisy pixels are replaced with the mean value of noise free pixel in selected window. In addition, the proposed filter (SUMF) uses simple fixed length window of size 2X2 which results in easy implementation.

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

2. Proposed Filter

In the proposed filter (SUMF) the mean value of noise free pixel in selected window is calculated and noisy pixels are replaced by mean of noise free pixels in selected window. The proposed filter is divided in two stages, first stage to indentify noisy pixels and second stage to remove noisy pixels. These two stages are described in the following subsections.

2.1. Stage (1). Noise Detection

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

Based on [1] and [14], it is assume that the two intensities that present the impulse noise are the maximum and the minimum values of the image 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).

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

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

2.2. Stage (2). Noise Removal

In this stage impulse noise is filtered by replacing noisy pixel with calculated mean value of noise free pixels in selected window. The proposed filter involves the following steps to remove the impulse noise:-

Step(1). Initialize the window size of the filter by 2×2 matrix.
Step(2). Find out the noise free pixels present in 2×2 matrix.
Step(3). Find out the mean value of the noise free pixels in selected window.
Step(4). Replace the noisy pixel by the calculated mean value in step (3).
Step(5). Repeat steps from 1- 4, to process the entire image for removal of impulse noise.

3. Simulation & Experimental Results

In order to demonstrate the performance of the proposed filter, it is tested on different gray scale natural images (i.e. 8-bit/pixel). The proposed filter (SUMF) 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 with different noise density ranging from 10% to 95%. The performance of proposed filter is expressed in terms of the peak signal to noise ratio (PSNR) and mean squared error (MSE). PSNR parameter estimates the quality of a reconstructed image with respect to original image. Reconstructed images with higher PSNR are better. PSNR is defined in equation (2).

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

Where MSE is mean squared error which is given by equation (3)

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

3.1. Experiment 1

Table 1 and Table 2 demonstrate the comparison of PSNR and MSE values of different filters for gray scale Lena image. The performance of proposed filter (SUMF) is compared with various previous 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 Table 1 and Table 2 that proposed filter gives better result in comparison to other existing techniques particularly for high density impulse noise. Fig. 1 and Fig. 2 illustrate the graphical comparison of PSNR & MSE performance metric for different filters for gray scale Lena image.

3.2. Experiment 2

In order to demonstrate the visual enhancement of proposed filter another experiment has been conducted on Lena & House images with the noise density (N.D.) ranging from 80% to 95%. The visual enhancement of proposed filter 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 image of size 512× 512 pixels are shown in Fig. 3(B), 3(C), 3(D), 3(E), 3(F), 3(G), 3(H), Fig. 4(B), 4(C), 4(D), 4(E), 4(F), 4(G), 4(H), Fig. 5(B), 5(C), 5(D), 5(E), 5(F), 5(G), 5(H), Fig. 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) and Fig. 8(B), 8(C), 8(D), 8(E), 8(F), 8(G), 8(H) with noise density 80%, 90% and 95% respectively. It is clear from Fig. 3 to Fig. 8 that the image recovered from the proposed filter is better than other noise removal algorithm in terms of visibility especially for higher noise density.

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

Algorithm / ND	SMF	PSMF	CWMF	OCS	DBA	MDBUTMF	SUMF
10%	33.25	36.82	32.42	29.60	35.62	37.95	**38.38**
20%	28.91	32.40	29.61	29.22	32.24	34.73	**34.52**
30%	23.63	28.94	27.18	28.62	30.02	32.39	**32.29**
40%	18.98	24.97	23.81	27.78	28.51	30.27	**30.18**
50%	15.29	20.48	20.43	26.76	26.99	28.19	**28.31**
60%	12.36	12.26	17.07	25.50	25.36	26.56	**26.72**
70%	9.97	9.95	13.96	24.03	22.83	24.13	**24.87**
80%	8.17	8.09	11.15	21.55	21.04	21.73	**22.78**
90%	6.68	6.65	8.72	18.30	18.11	18.62	**20.24**
95%	5.98	5.99	7.64	16.22	16.56	17.22	**18.52**

Table 2: Comparative MSE of different filters for lena.png (Gray scale Image)

Algorithm / ND	SMF	PSMF	CWMF	OCS	DBA	MDBUTMF	SUMF
10%	30.78	13.53	37.21	71.24	17.82	10.42	**9.42**
20%	83.49	37.46	71.13	77.90	38.82	21.88	**23.01**
30%	281.91	83.07	124.20	89.25	62.09	37.50	**38.21**
40%	822.30	206.84	270.32	108.40	91.63	61.10	**62.32**
50%	1925.19	582.64	588.05	137.09	130.04	98.64	**96.08**
60%	3774.38	3860.23	1270.0	183.22	189.26	143.57	**138.13**
70%	6545.43	6577.23	2610.23	257.36	338.90	251.23	**211.08**
80%	9902.36	10088.95	4930.12	454.67	511.77	436.59	**343.06**
90%	13962.06	14068.25	8720.21	962.27	1004.81	893.47	**614.84**
95%	16412.70	16374.33	11196.45	1552.25	1435.75	1233.34	**914.28**

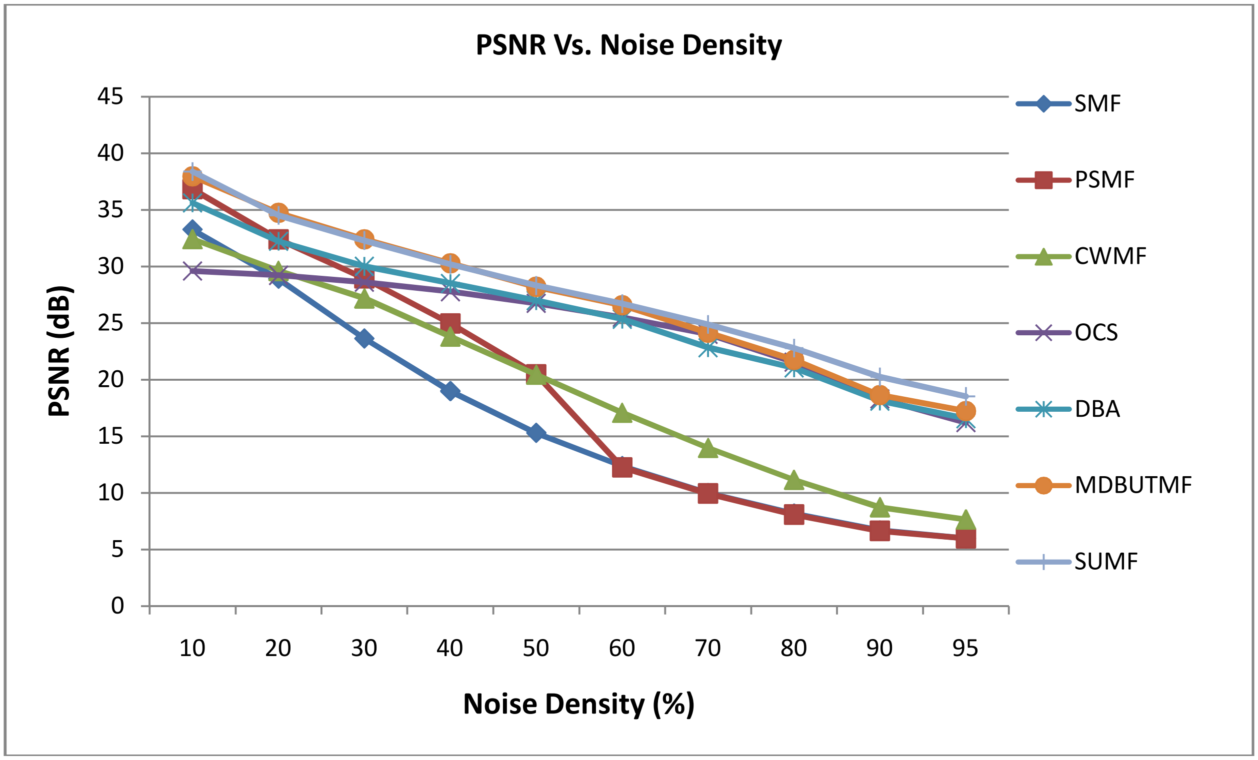

Fig. 1. PSNR Vs Noise Density for Lena Image

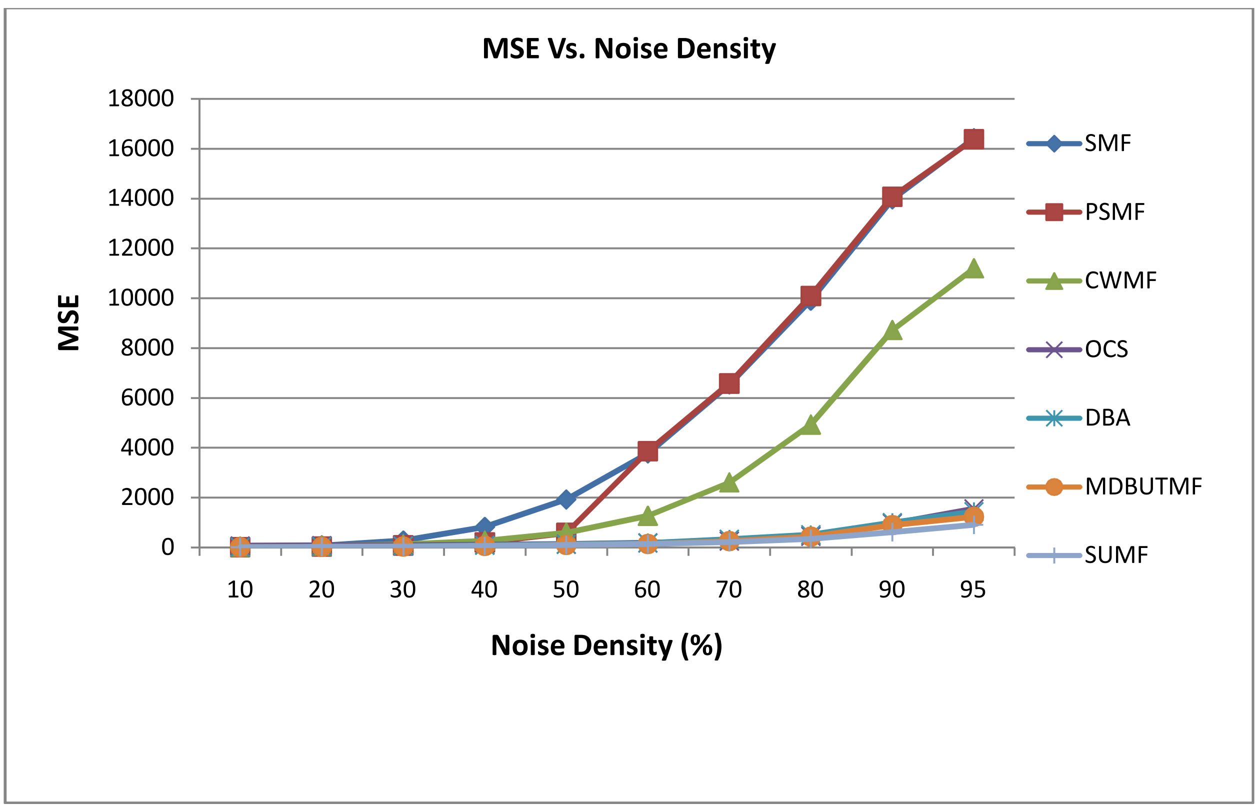

Fig. 2. MSE Vs Noise Density for Lena Image.

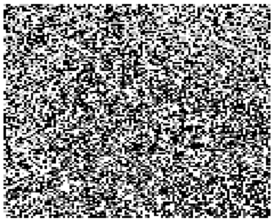
Fig. 3(A). Noisy image with noise density 80%

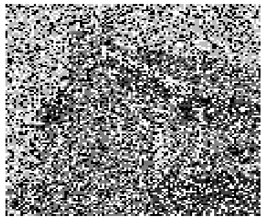
Fig. 3 (B). Output of SMF

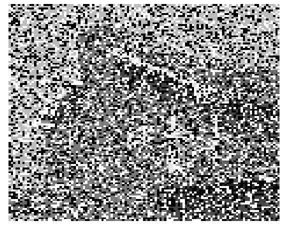
Fig. 3(C). Output of PSMF

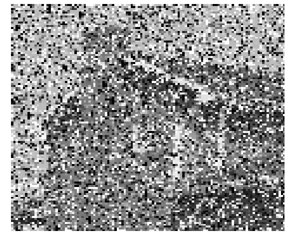
Fig. 3(D). Output of CWMF

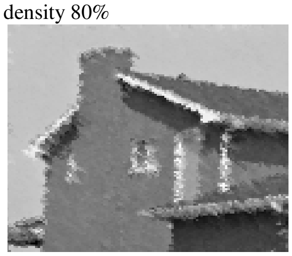
Fig. 3(E).Output of OCSF


Fig. 3(F). Output of DBA


Fig. 3(G). Output of MDBUTMF


Fig. 3(H). Output of SUMF

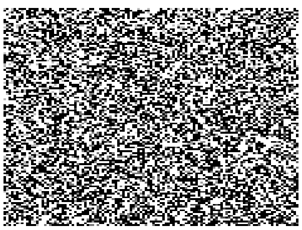
Fig. 4 (A). Noisy image with noise density 90%

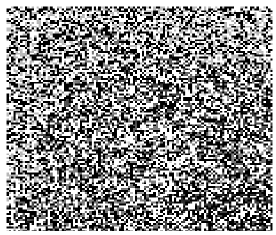
Fig. 4(B). Output of SMF

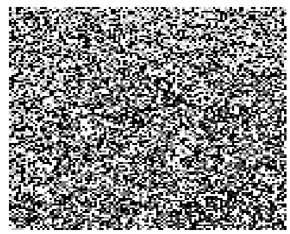
Fig. 4(C). Output of PSMF

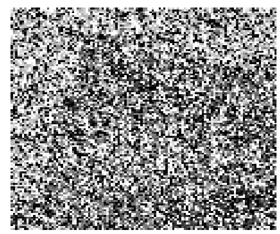
Fig.4(D). Output of CWMF

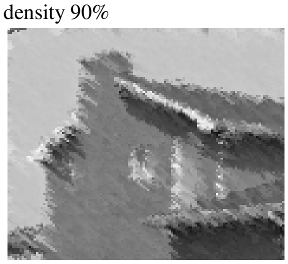
Fig. 4(E).Output of OCSF


Fig. 4 (F). Output of DBA


Fig. 4 (G). Output of MDBUTMF

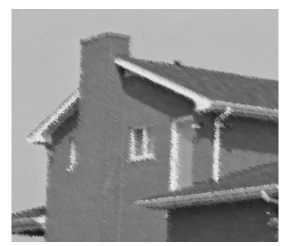
Fig. 4 (H). Output of SUMF

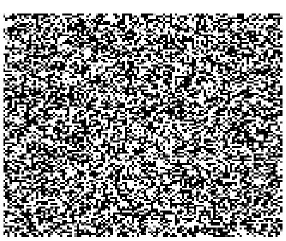
Fig. 5(A). Noisy image with noise density 95%

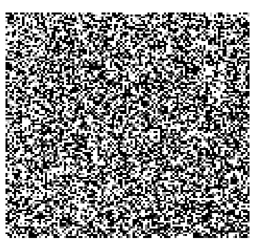
Fig. 5(B). Output of SMF

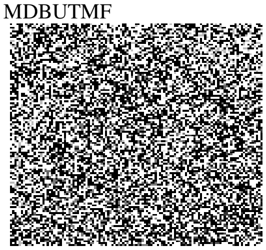
Fig. 5(C). Output of PSMF

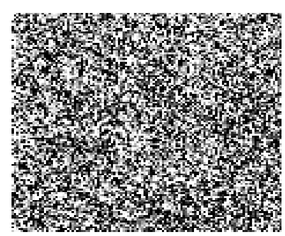
Fig.5(D). Output of CWMF

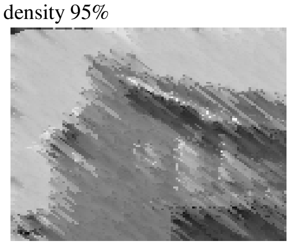
Fig. 5(E).Output of OCSF

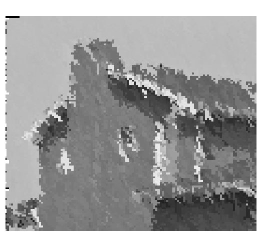
Fig. 5 (F). Output of DBA


Fig. 5(G). Output of MDBUTMF


Fig. 5(H). Output of SUMF


Fig. 6(A). Noisy image with noise density 80%

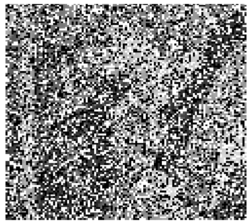
Fig. 6(B). Output of SMF

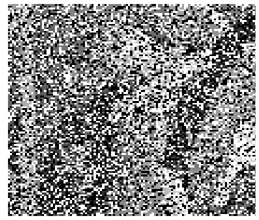
Fig. 6(C). Output of PSMF


Fig. 6(D). Output of CWMF

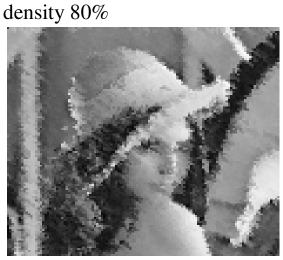
Fig. 6(E).Output of OCSF


Fig. 6(F). Output of DBA


Fig. 6(G). Output of MDBUTMF


Fig. 6(H). Output of SUMF

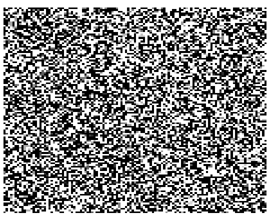
Fig. 7(A). Noisy image with noise density 90%

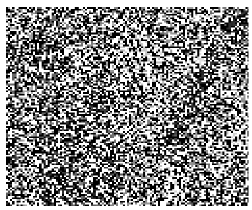
Fig. 7(B). Output of SMF

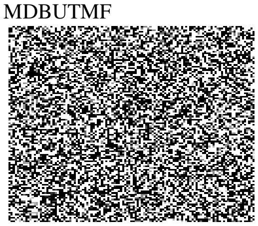
Fig. 7(C). Output of PSMF

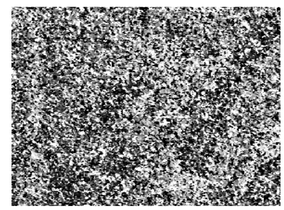
Fig.7(D). Output of CWMF

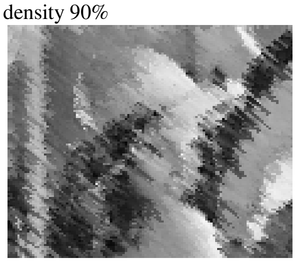
Fig. 7(E).Output of OCSF


Fig. 7(F). Output of DBA


Fig. 7(G). Output of MDBUTMF

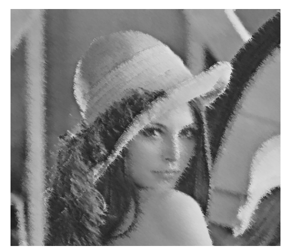
Fig. 7(H). Output of SUMF

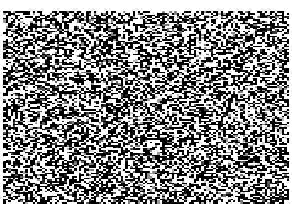
Fig. 8(A). Noisy image with noise density 95%


Fig. 8(B). Output of SMF

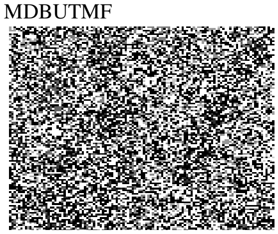
Fig. 8(C). Output of PSMF

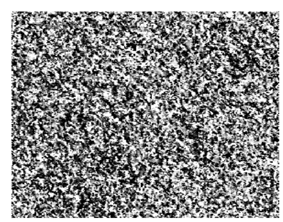
Fig. 8(D). Output of CWMF

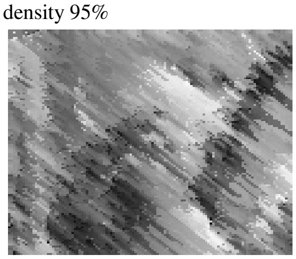
Fig. 8(E).Output of OCSF

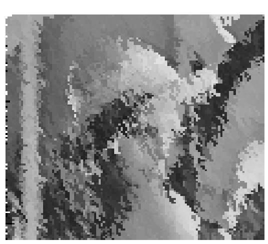
Fig. 8(F). Output of DBA

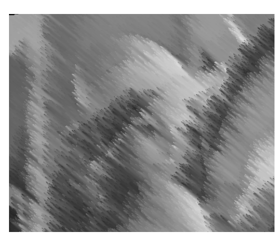
Fig. 8(G). Output of MDBUTMF

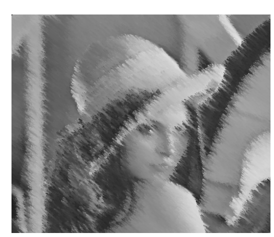
Fig. 8(H). Output of SUMF

4. Conclusion

The proposed SUMF filter has been used to remove high density salt & pepper noise from digital natural images. The proposed SUMF filter has been tested on different gray scale natural images. The performance of proposed SUMF filter has been evaluated in terms of PSNR and MSE. The performance of proposed SUMF filter has been compared to other many existing denoising filters and algorithms 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 proposed SUMF filter has provided better performance as compared to other many existing denoising filters and algorithms even at 95% noise density levels. Both visual and quantitative results have been demonstrated. The proposed SUMF filter has effective for impulse noise (salt and pepper) removal from images at high noise densities.

References

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