

An Efficient Adaptive Mean Filtering Technique for Removal Of Salt And Pepper Noise From Images

Bibekananda Jena¹, Punyaban Patel², C R Tripathy³

^{1,2}Purushottam Institute of Engineering and Technology, Rourkela, India

³Department of CSE, VSSUT, Burla, India

Abstract- Most of the paper published so far are using median filter for removing salt and pepper noise from digital images. The novelty of the proposed efficient adaptive mean filtering (EAMF) scheme is that it uses mean value of dynamic window size instead of median value for filtering of high density noisy images without blurring. This filter replaces the noisy pixels with the mean value of non-noisy neighbouring pixels selected from a window dynamically. If the number of non-noisy pixels in the selected window is not sufficient, a window of next higher size is chosen. Thus window size is automatically adapted based on the density of noise in the image as well as the density of corruption local to a window. As a result window size may vary pixel to pixel while filtering. The efficacy of the proposed scheme is evaluated with respect to subjective as well as objective parameters on standard images on various noise densities. Comparative studies proves that the proposed method removes the salt and pepper noise effectively with better image quality compared with conventional methods and recently proposed methods such as Tolerance Based Selective Arithmetic Mean Filtering Technique (TSAMFT), Efficient Decision Based Algorithm (EDBA), Improved Efficient Decision-Based Algorithm (IDBA), Robust Estimation Based Filter (REBF), Novel Improved Median Filter (NIMF) and Modified Decision Based Un-Symmetric Trimmed Median Filter (MDBUTMF). The visual and quantitative results show that the performance of the proposed filter in the preservation of edges and details is better even at noise level as high as 95%.

Keywords:

Impulse Noise; Image Denoising; Adaptive filter; Peak Signal-to-Noise Ratio (PSNR); signal-to-noise ratio (SNR); Improve Peak Signal-to-Noise Ratio (ISNR); Mean Square Error (MSE); Image Quality Index (IQI);

I. INTRODUCTION

Salt-and-pepper noise is a special case of impulse noise, where a certain percentage of individual pixels in digital image are randomly digitized into two extreme intensities. Normally, these intensities are called maximum and minimum intensity. The contamination of digital image by salt-and-pepper noise is largely caused by error in image acquisition and/or recording. For example, faulty memory locations or impaired pixel sensors can result in digital image being corrupted with salt-and-pepper noise [4].

Emergent techniques based on Fuzzy Logic have successfully entered the area of nonlinear filters. Indeed, a variety of methods have been recently proposed in the literature which are able to perform detail-preserving smoothing of noisy image data yielding better results than classical operators. Since the first introduction of Fuzzy Set Theory [1] fuzzy techniques for image processing applications have mainly dealt with high-level computer vision and pattern recognition [2].

In traditional median filtering [3] called standard median filter (SMF), the filtering operation is performed across to each pixel without considering whether it is uncorrupted. So, the image details, contributed by the uncorrupted pixels are also subjected to filtering and as a result the image details are lost in the restored version. To alleviate this problem, an impulse noise detection mechanism is applied prior to the image filtering. In switching median filters [10,11], a noise detection mechanism has been incorporated so that only those pixels identified as "corrupted" would undergo the filtering process, while those identified as "uncorrupted" would remain intact. The progressive switching median filter (PSMF) [5] was proposed which achieves the detection and removal of impulse noise in two separate stages. In first stage, it applies impulse detector and then the noise filter is applied progressively in iterative manners in second stage. In this method, impulse pixels located in the middle of large noise blotches can also be properly detected and filtered. The performance of this method is not good for very highly corrupted image. Nonlinear filters such as adaptive median filter (AMF) [6] can be used for discriminating corrupted and uncorrupted pixels and then apply the filtering technique. Noisy pixels will be replaced by the median value, and uncorrupted pixels will be left unchanged. AMF performs well at low noise densities but at higher noise densities, window size has to be increased to get better noise removal which will lead to less correlation between corrupted pixel values and replaced median pixel values. An efficient decision-based algorithm (DBA) was proposed [7] using a fixed window size of 3×3 , where the corrupted pixels are replaced by either the median pixel or neighbourhood pixels. It shows promising results, a smooth transition between the pixels is lost with lower processing time which degrades the visual quality of the image. To overcome this problem, an improved decision-based algorithm (IDBA) [8] is proposed where corrupted pixels can be replaced either by the median pixel or, by the mean of processed pixels in the neighbourhood. It results in a smooth transition between the pixels with edge preservation and better visual quality for low-density impulse noise. The limitation of this method is that in the case of high-density impulse noise, the fixed window size of 3×3 will result in image quality degradation due to the presence of corrupted pixels in the neighbourhood. The minimum-maximum exclusive mean (MMEM) [12] filter is presented to remove impulse noise from highly corrupted images. Simulation results show that even if the occurrence rate of the impulse noise is very high (70%), the restoration performance is still acceptable. A novel method for removing

fixed value impulse noise using robust estimation based filter (REBF) [13] is proposed. The function of the proposed filter is to detect the outlier pixels and restore the original value using robust estimation. A Novel Improved Median Filter (NIMF) for Salt-and-Pepper Noise from Highly Corrupted Images have been proposed [14], which has better performance for noise removal adaptively, and detail preservation, especially effective for the cases when the images are extremely highly corrupted. A Removal of High Density Salt and Pepper Noise through Modified Decision Based Unsymmetric Trimmed Median Filter (MDBUTMF) [15] is proposed for the restoration of grey scale, and colour corrupted by salt and pepper noise. It replaces the noisy pixel by trimmed median value when other pixel values, 0's and 255's are present in the selected window and when all the pixel values are 0's and 255's then the noise pixel is replaced by mean value of all the elements present in the selected window.

Most of the schemes discussed above use a fixed window size and median value for noise filtering. The window size is larger in high density impulse noise and smaller in low density noise. Use of fixed window size for noise filtering in digital image is an unrealistic assumption, because in real time applications the percentage of corruption is unknown. Filtering each and every pixel of a high density noisy image with a fixed large window, without the knowledge of number of non-noisy neighboring pixel, not only produce distortion but also takes more execution time. So a scheme of dynamic window size must be adopted for a test pixel based on the density of corruption in its neighboring pixels. The optimal window size for filtering is selected based on the presence of non-noisy neighbours in the window. In this paper, we propose an Efficient Adaptive Mean Filter (EAMF) for removing high density salt and pepper noise. This scheme only filters the pixels having value '0' or '255'. At the beginning of the filtering process, the scheme decides the window size for the test pixel locally and is adaptive due to the selection of a proper window size during run time. As the non-noisy neighbours of the pixel in the current window is used for filtering, we are using a mean filter instead of a median filter which can work better both in low as well as high density noise.

The outline of this paper is as follows; Section 2 deals with the noise model. In Section 3 deals with Performance Measures; In Section 4 Proposed Method; In Section 5 the simulation results along with comparative analysis are discussed in detail. Finally, Section 6 gives the concluding remarks.

II. NOISE MODEL

Impulsive noise can be classified as salt-and-pepper noise (SPN) and random-valued impulse noise (RVIN). An image containing impulsive noise can be described as follows:

$$x(i,j) = \begin{cases} \eta(i,j) & \text{with probability } p \\ y(i,j) & \text{with probability } 1 - p \end{cases} \quad (1)$$

$x(i,j)$ denotes a noisy image pixel, $y(i,j)$ denotes a noise free image pixel and $\eta(i,j)$ denotes a noisy impulse at the location (i,j) . In salt-and-pepper noise, noisy pixels take either minimal or maximal values i.e. $\eta(i,j) \in \{L_{min}, L_{max}\}$ and for random-valued impulse noise, noisy pixels take any value within the range minimal to maximal value i.e. $\eta(i,j) \in [L_{min}, L_{max}]$, where L_{min}, L_{max} denote the lowest and the highest pixel luminance values within the dynamic range respectively. So that it is little bit difficult to remove random valued impulse noise rather than salt and pepper noise [3]. The main difficulties, which have to face for attenuation of noise, is the preservation of image details. Figure-1 may best describe the difference between SPN and RVIN. In the case of SPN the pixel substitute in the form of noise may be either $L_{min}(0)$ or $L_{max}(255)$. Where as, in RVIN situation it may range from L_{min} to L_{max} . Cleaning such noise is far more difficult than cleaning fixed-valued impulse noise since for the later, the differences in gray levels between a noisy pixel and its noise-free neighbours are significant most of the times. In this paper, we focus only on salt-and-pepper noise and schemes are proposed to eliminate such noises.

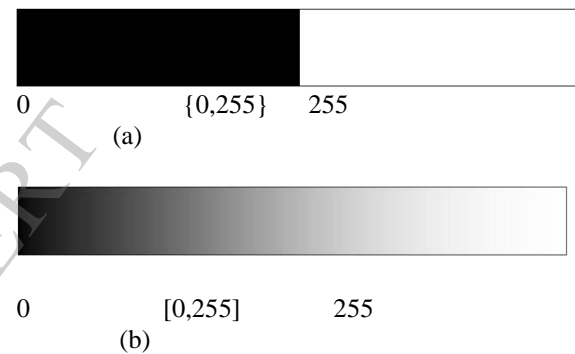


Figure 1: Representation of (a) Salt & Pepper Noise with $R_{i,j} \in \{n_{min}, n_{max}\}$ (b) Random Valued Impulsive Noise with $R_{i,j} \in [n_{min}, n_{max}]$

III. PERFORMANCE MEASURES

There are basically two classes through which we can measure the performance and quality of an image. These are Objective quality and the Subjective or Qualitative or Distortion measure. The metrics used for performance comparison among different filters are defined below:

A. Objective Quality

1) Mean Squared Error (MSE) And Mean Absolute Error

In statistics, the mean squared error or MSE of an estimator is one of many ways to quantify the amount by which an estimator differs from the true value of the quantity being estimated. Here, it is just used to calculate the difference between an original image with a restored image. Given that

original image X of size $(M \times N)$ pixels and as reconstructed image \hat{X} , the MSE is defined as:

$$MSE = \frac{1}{M \times N} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} (X_{ij} - \hat{X}_{ij})^2 \quad (2)$$

$$MAE = \frac{1}{MN} \sum_{ij} |X_{ij} - \hat{X}_{ij}| \quad (3)$$

2) Peak Signal to Noise Ratio (PSNR)

PSNR analysis uses a standard mathematical model to measure an objective difference between two images. It estimates the quality of a reconstructed image with respect to an original image. Reconstructed images with higher PSNR are judged better. Given that original image X of size $(M \times N)$ pixels and as reconstructed image \hat{X} , the PSNR (dB) is defined as:

$$PSNR(dB) = 10 \log_{10} \left(\frac{255^2}{MSE} \right) \quad (4)$$

3) Improved Peak Signal to Noise Ratio (ISNR)

For the purpose of objectively testing the performance of the restored image, Improvement in signal to noise ratio (ISNR) is used as the criteria which is defined by

$$ISNR = 10 \log \frac{\sum_{ij} [X_{ij} - Y_{ij}]^2}{\sum_{ij} [X_{ij} - \hat{X}_{ij}]^2} \quad (5)$$

Where j and i are the total number of pixels in the horizontal and vertical dimensions of the images X_{ij} , Y_{ij} and \hat{X}_{ij} are the original, degraded and the restored image respectively.

4) Structural Similarity Index Measure (SSIM)

The Structural Similarity Index Measure (SSIM) [16] between the original image and restored image can be defined by,

$$SSIM = L(X, \hat{X}) * C(X, \hat{X}) * S(X, \hat{X}) \quad (6)$$

Where,

$$\begin{aligned} L(X, \hat{X}) &= (2\mu_X \mu_{\hat{X}} + C_1) / (\mu_X^2 + \mu_{\hat{X}}^2 + C_1) \\ C(X, \hat{X}) &= (2\sigma_X \sigma_{\hat{X}} + C_2) / (\sigma_X^2 + \sigma_{\hat{X}}^2 + C_2) \\ S(X, \hat{X}) &= (\sigma_{X\hat{X}} + C_3) / (\sigma_X \sigma_{\hat{X}} + C_3) \\ C_1 &= (K_1 * G)^2, C_2 = (K_2 * G)^2, C_3 = C_2/2 \\ G &= 255 \text{ (for 8 bit image)}, K_1, K_2 \ll 1, \\ (K_1 &= 0.001, K_2 = 0.001) \end{aligned}$$

Where, X is the original Image, \hat{X} is the restored image, Y is the corrupted image, $M \times N$ is the size of the image, L is the luminance comparison, C is the contrast comparison, S is the structure comparison, μ is the mean and σ is the standard deviation.

B. Subjective Measure

Along with the above performance measure subjective assessment is also required to measure the image quality. In a subjective assessment measures characteristics of human perception become paramount, and image quality is correlated with the preference of an observer or the performance of an operator for some specific task. The qualitative measurement approach does not depend on the image being tested, the viewing conditions or the individual observer.

In this paper, we also used a qualitative-based performance measure through the metric named image quality index (IQI) to prove the efficiency of our proposed algorithm. It was proposed by Wang and Bovik [16], which is easy to calculate and applicable to various image processing applications. This quality index models any distortion as a combination of three different factors: loss of correlation, luminance distortion, and contrast distortion. IQI [9,16] can be defined as below:

$$IQI_j = Corr(X, \hat{X}) * Lum(X, \hat{X}) * Cont(X, \hat{X}) \quad (7)$$

$$Corr(X, \hat{X}) = \sigma_{X\hat{X}} / \sigma_X \sigma_{\hat{X}}$$

$$Lum(X, \hat{X}) = 2\mu_X \mu_{\hat{X}} / (\mu_X^2 + \mu_{\hat{X}}^2)$$

$$Cont(X, \hat{X}) = 2\sigma_X \sigma_{\hat{X}} / (\sigma_X^2 + \sigma_{\hat{X}}^2)$$

IQI is first applied to local regions using a sliding window approach with size $w \times w$. The X_w and \hat{X}_w represents the sliding window of original and restored images, respectively. Here, we have taken $w = 8$. At the j^{th} step, the local quality index IQI_j is computed within the sliding window using the formula given above. If there are total of M steps, then the overall image quality index is given by,

$$IQI = (1/M) \sum_j IQI_j \quad (8)$$

Where, j varies from 1 to M . The dynamic range of IQI is $[-1, 1]$, and the best value 1 is achieved if and only if restored image \hat{X} is equal to the original image X .

IV. PROPOSED METHOD

The proposed EAMF is an adaptive non-recursive mean filter removes impulse noise even for higher noise densities without much blurring and retains the edges and fine details. It contains a simple noise detection stage at the beginning of the

EAMF Algorithm:*Input : the noisy image Y* *Output: The filtered image \hat{X}*

- Step 1. Initialize a sub-window size, $W=3$ and maximum window size, $W_{\max}=13$
- Step 2. Select a sub-window $W \times W$ with center pixel x_{ij} .
- Step 3. If x_{ij} is not equal to 0 or 255, shift the window and go to Step 1
- Step 4. Collect the set of pixels (S) from the sub-window ignoring the pixels of intensity value '0' or '255'.
- Step 5. If the size of $S \geq 1$, do
- Replace x_{ij} with mean of pixels in S .
 - Shift the window
 - Go to Step -1
- Else go to step -6
- Step 6. $W=W+2$;
- Step 7. If $W \leq W_{\max}$, go to Step 2, else replace the center pixel by mean of all the pixels in the sub-window of size W_{\max}
- Step 8. Repeat Step 2 through Step 7 for all pixels in the image.

filtering operation by inspecting the pixel value. If it is lies within the minimum (0) and maximum (255) gray level value, it is considered as a noise free pixel and remain untreated. If the pixel matches with any of the minimum or maximum value, it is considered as a noisy pixel and processed by the proposed filtering method. The filtering stage starts with a 3×3 window which is applied on the noisy pixel only. Once a pixel identified as noisy then the mean of the non-noisy neighbours of the current window is used to restore the

detected noisy pixel. If the selected window contains all the elements as noisy, the size of window is increased to 5×5 and the process is repeated till the window size reaches to a predefined maximum window size. The algorithm automatically chooses the optimal window size. The maximum window size is not allowed to exceed 13×13 which drastically reduced the computation time and preserves the edge details in the case of high-density impulse. The steps of the EAMF algorithm are given below.

V. SIMULATION AND RESULT:

To validate the proposed scheme EAMF, simulation has been performed on standard images, likes Lena, Boat of size 512×512 . The images are subjected to as low as 10% noise density to as high as 95% noise density. The proposed scheme as well as the recently suggested few well performing schemes like SMF, PSMF, AMF, MMEM, DBA, IDBA, REBF, NIMF, MDBUTMF are applied to the noisy images. The simulation is carried out using MATLAB 7.0. There are basically two classes of metrics like Objective quality and the Subjective or Qualitative or Distortion measure through which performance measure and quality of restored image are evaluated to show the efficacy of the proposed scheme as compared to other standard and recently proposed schemes. The performance measures discussed above are used to prove the superiority of the proposed method.

The performance parameter values such as PSNR, ISNR and IQI obtained after applying the various filters are compared by varying the noise density from 10% to 95% are shown in Table-1, Table-2, and Table-3 respectively. From the quantitative values shown in the tables, it is very clear that EAMF algorithm outperforms all other noise removal filters.

Table 1: Comparative Analysis of PSNR For Various Filters In Lena Image

% of Noise	PSNR (dB)									
	SMF	PSMF	AMF	MMEM	DBA	IDBA	REBF	NIMF	MDBU TMF	EAMF
10	34.3624	36.8431	39.5265	38.3719	39.0850	39.6600	40.1244	41.1079	44.4576	44.0265
20	29.5833	33.2382	34.8684	37.3380	36.5952	36.8526	38.4960	37.8598	40.3986	40.5192
30	23.8910	30.9431	32.3878	36.1709	34.2939	34.5395	36.9595	35.9931	37.7772	38.2512
40	19.0081	27.5024	30.2430	34.8999	32.2594	32.6563	35.4830	34.5501	35.4653	36.4703
50	15.2828	26.2964	28.4616	33.9148	30.3886	31.0516	34.0558	33.4518	32.8599	35.0722
60	12.2427	24.8570	26.8338	32.5245	28.4584	29.3937	32.5071	32.1821	29.0700	33.4347
70	9.9588	20.9470	25.0211	30.7746	26.3646	28.0187	30.7451	30.7815	24.5225	31.5785
80	8.1050	13.7021	23.2912	29.0498	23.7943	25.9108	28.9096	29.2726	20.0322	29.6500
90	6.5740	7.7175	20.6217	26.2669	20.1332	22.6076	26.4006	26.5751	15.6034	27.0937
95	5.9249	6.0266	17.9292	23.5006	17.1567	19.9613	24.4896	23.8902	13.5834	25.0140

Table 2: Comparative Analysis of ISNR For Various Filters In Lena Image

ISNR , Lena.jpg										
% of Noise	SMF	PSMF	AMF	MMEM	DBA	IDBA	REBF	NIMF	MDBU TMF	EAMF
10	19.0175	21.4981	24.1815	23.0269	23.7401	24.3210	24.7795	25.7629	29.1126	28.6815
20	17.2402	20.8950	22.5252	24.9948	24.2520	24.5094	26.1529	25.5166	28.0555	28.1760
30	13.2915	20.3437	21.7884	25.5715	23.6944	23.9400	26.3601	25.3937	27.1778	27.6517
40	9.6699	18.1642	20.9048	25.5617	22.9212	23.3181	26.1448	25.2119	26.1271	27.1321
50	6.9135	17.9271	20.0924	25.5455	22.0194	22.6823	25.6866	25.0825	24.4906	26.7030
60	4.6752	17.2895	19.2661	24.9570	20.8908	21.8262	24.9395	24.6146	21.5025	25.8672
70	3.0471	14.0353	18.1094	23.8629	19.4529	21.1070	23.8335	23.8698	17.6109	24.6668
80	1.7648	7.3618	16.9510	22.7096	17.4541	19.5706	22.5694	22.9324	13.6821	23.3100
90	0.7558	1.8589	14.8027	20.4480	14.3143	16.7886	20.5817	20.7562	9.7844	21.2748
95	0.3427	0.4444	12.3470	17.9184	11.5745	14.3791	18.9074	18.3080	8.0012	19.4318

Table 3: Comparative Analysis of IQI For Various Filters In Lena Image

ISNR , Lena.jpg										
% of Noise	SMF	PSMF	AMF	MMEM	DBA	IDBA	REBF	NIMF	MDBU TMF	EAMF
10	19.0175	21.4981	24.1815	23.0269	23.7401	24.3210	24.7795	25.7629	29.1126	28.6815
20	17.2402	20.8950	22.5252	24.9948	24.2520	24.5094	26.1529	25.5166	28.0555	28.1760
30	13.2915	20.3437	21.7884	25.5715	23.6944	23.9400	26.3601	25.3937	27.1778	27.6517
40	9.6699	18.1642	20.9048	25.5617	22.9212	23.3181	26.1448	25.2119	26.1271	27.1321
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80	1.7648	7.3618	16.9510	22.7096	17.4541	19.5706	22.5694	22.9324	13.6821	23.3100
90	0.7558	1.8589	14.8027	20.4480	14.3143	16.7886	20.5817	20.7562	9.7844	21.2748
95	0.3427	0.4444	12.3470	17.9184	11.5745	14.3791	18.9074	18.3080	8.0012	19.4318

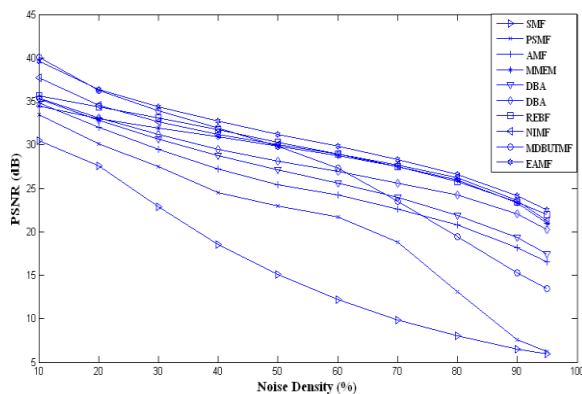


Figure 2: PSNR vs Noise Density(%) of Boat image

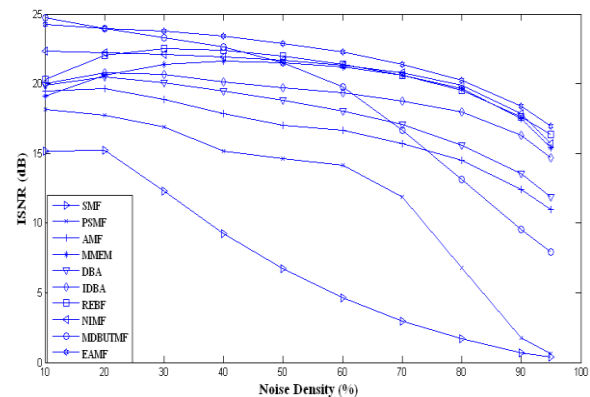


Figure 3: ISNR vs Noise Density(%) of Boat image

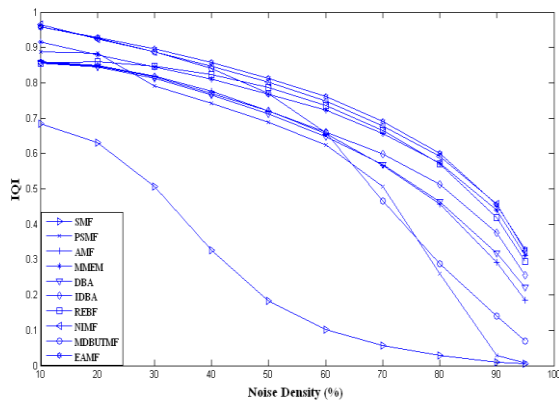


Figure 4: IQI vs Noise Density(%) of Boat image

The PSNR and ISNR of the Restored images obtained from different existing scheme mentioned above simulated along with the proposed method and plotted in Figures 2 and 3 for Boat image respectively. The IQI values of the same are plotted in Figure 4. It has been observed that the proposed scheme at low as well as high noise density is superior to all other schemes. In addition to the IQI value, the image quality map has also been generated to evaluate the performance of the different algorithms. Brighter image quality map (closer to 1) indicates that the restored image is closer to the original image, and darker image quality map indicates that the restored image is more distant from the original image. Figure 5 shows their restored image and the corresponding image quality map of various filters applied on noisy images of 30%, 60% and 90% noise density. Figure 6 shows that the image quality map of the proposed method is brighter as compared to others for low as well as high density salt and pepper noise.

To verify the effectiveness of the proposed method for very high density noise, an experiment has been carried on images corrupted with 95% of salt and pepper noise. Figure 6 shows the result of various filters for salt-and-pepper image of 95% noise density.

VI. CONCLUSION

In this paper, we propose a mean filtering scheme, namely, EAMFT to recover images corrupted with high density salt and pepper noise. The filter works in two phases, namely, identification of corrupted locations followed by the filtering operation. The window size for any test pixel is selected adaptively utilizing the local information from its neighbours. Subsequently, it applies the mean filter considering only the non-corrupted neighbours in the window. The linear combination of the center pixel and the mean value is used to replace the noisy pixel value. The performance of the algorithm has been tested at low, medium and high noise densities on different standard grey scale images. The proposed scheme is evaluated both qualitatively as well as

quantitatively. The comparative performance analysis in general shows that the proposed scheme outperforms the existing schemes both in terms of noise reduction and retention of image details at high densities impulse noise.

REFERENCES

- [1] L. A. Zadeh, "Fuzzy sets", *Information and Control*, vol. 8, pp. 338-353, 1965.
- [2] J. C. Bezdek and S. K. Pal, *Fuzzy models for pattern recognition*, IEEE Press, 1992.
- [3] Gonzalez R.C, Woods R.E., "Digital Image Processing", 3rd edition, Pearson Education, 2009.
- [4] K. K. V. Toh, H. Ibrahim, and M. N. Mahyuddin, "Salt-and-peppernoise detection and reduction using fuzzy switching median filter," *IEEE Trans. Consumer Electron.*, vol. 54, no. 4, pp. 1956-1961, Nov. 2008.
- [5] Zhou Wang and David Zhang, "Progressive Switching Median Filter for the Removal of Impulse Noise from Highly Corrupted Images", *IEEE Transactions On Circuits And Systems—II: Analog And Digital Signal Processing*, Vol. 46, No. 1, pp. 78-80, January 1999.
- [6] Raymond H. Chan, Chung-Wa Ho, and Mila Nikolova, "Salt-and-Pepper Noise Removal by Median-type Noise Detectors and Detail-preserving Regularization", *IEEE Trans. Image Process.*, vol. 14, no. 10, pp. 1479-1485, Oct. 2005.
- [7] Srinivasan, K.S., Ebenezer, D., "A new fast and efficient decision based algorithm for removal of high-density impulse noises", *IEEE Signal Process. Lett.* 14(3), Pp. 189-192, 2007.
- [8] Madhu N.S., Revathy K., Tatavarti, R., "Removal of Salt-and-Pepper Noise in Images: A New Decision-Based Algorithm", In: *Proceedings of IAENG International Conference on Imaging Engineering—ICIE 2008, IAENG International Multiconference of Engineers and Computer Scientists—IMECS 2008*, pp. 611-616. Lecture Notes in Engineering and Computer Science 1, Hong Kong, 2008.
- [9] Madhu S. Nair and G. Raju, "A new fuzzy-based decision algorithm for high-density impulse noise removal", *SIVIP*, 2010.
- [10] Eng, H.-L., Ma, K.-K. "Noise adaptive soft-switching median filter", *IEEE Trans. Image Process.* 10(2), Pp. 242-251, 2001.
- [11] G. Pok and J.-C. Liu, "Decision based median filter improved by predictions", *Proc. ICIP*, vol. 2, pp. 410-413, 1999.
- [12] Wei-Yu Han and Ja-Chen Lin, "Minimum-maximum exclusive mean (MMEM) filter to remove impulse noise from highly corrupted images", *ELECTRONICS LETTERS*, pp. 124 - , 16th January 1997 Vol. 33 No. 2.
- [13] V.R. Vijaykumar, P.T. Vanathi, P. Kanagasabapathy and D. Ebenezer, "High Density Impulse Noise Removal Using Robust Estimation Based Filter (REBF)", *International Journal of Computer Science*, 35:3, IJCA_35_3_02, 2008.
- [14] Changhong Wang, Taoyi Chen, and Zhenshen Qu, "A Novel Improved Median Filter (NIMF) for Salt-and-Pepper Noise from Highly Corrupted Images", pp. 718-722, IEEE.
- [15] S. Esakkirajan, T. Veerakumar, Adabala N. Subramanyam, and C. H. Prem Chand, "Removal of High Density Salt and Pepper Noise Through Modified Decision Based Unsymmetric Trimmed Median Filter (MDBTMMF)", *IEEE Signal Processing Letters*, Vol. 18, No. 5, May 2011.
- [16] Zhou Wang, "A Universal Image Quality Index", *IEEE Signal Processing Letters*, Vol. XX, No. Y, March 2002.

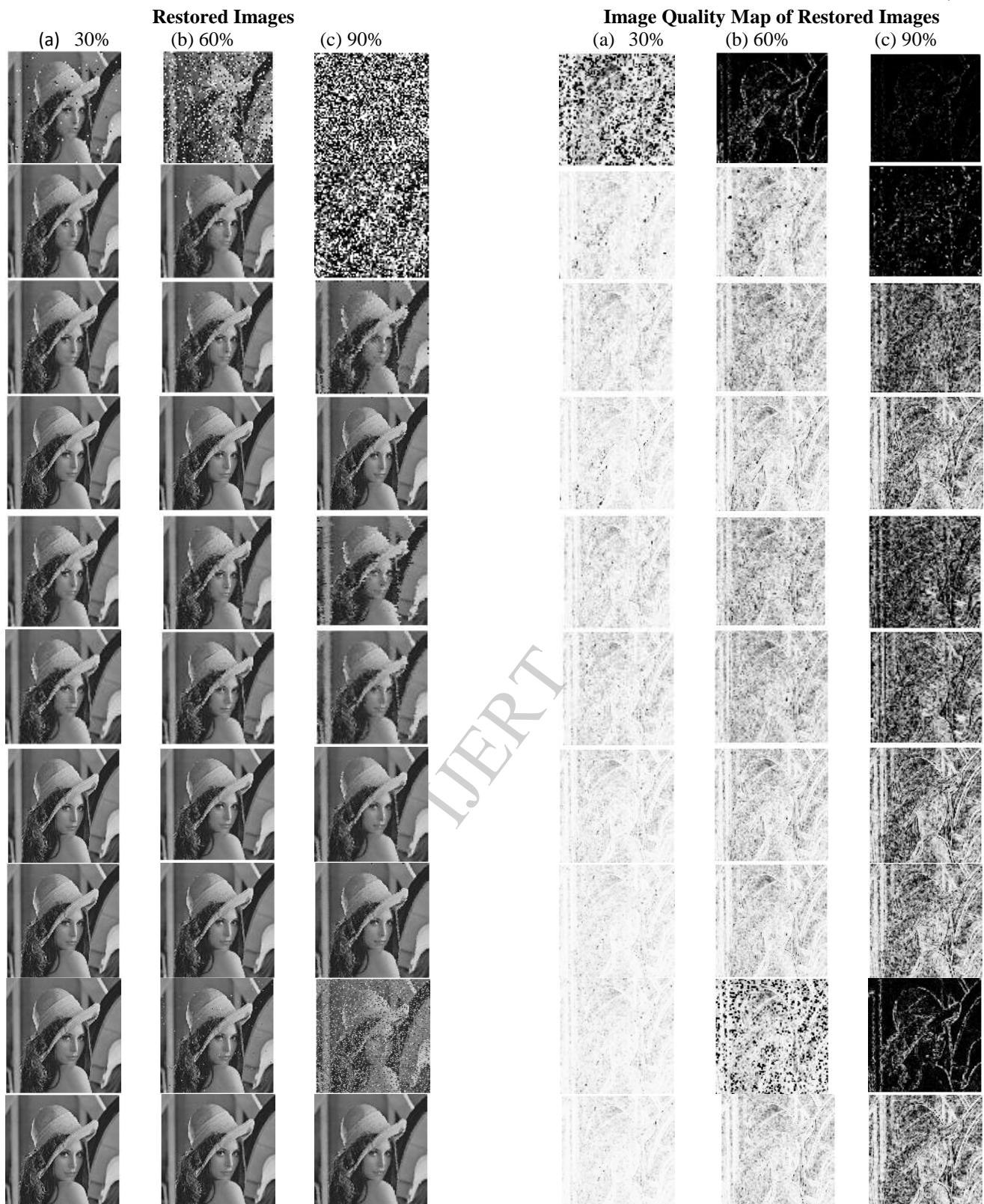


Fig. 5: Column a, b and c represent the restored images of Lena image corrupted with 30%, 60% and 90% noise respectively. Column d, e and f represent the corresponding image quality map. Rows 1, 2, 3, 4, 5, 6, 7, 8, 9 and 10 represents the restored images after applying the SMF, PSMF, AMF, MMEM, DBA, IDBA, REBF, NIMF, MDBUTMF and the proposed EAMF filters respectively.

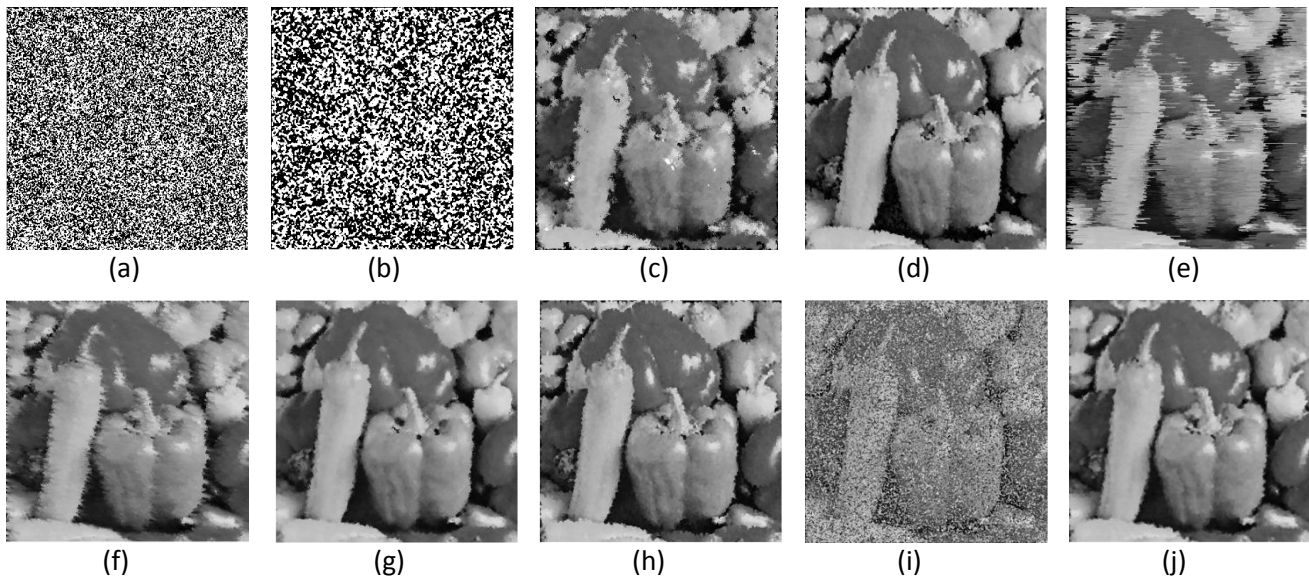


Fig. 6: Results of various filters for peppers image corrupted by 95% noise densities. (a)Output of SMF, (b) Output of PSMF, (c) Output of AMF, (d) Output of MEM, (e) Output of DBA, (f) Output of IDBA, (g) Output of REBF, (h) Output of NIMF, (i) Output of MDBUTMF, (j) Output of proposed EAMF