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Fuzzy Based Adaptive Mean Filtering Technique for Removal of Impulse Noise from Images

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Abstract

This paper proposes an fuzzy based adaptive mean filtering (FBAMF) scheme to remove high density impulse noise from images. The FBAMF is a two-stage filter where, in the first stage, a fuzzy detection technique is used to differentiate between corrupted and uncorrupted pixel by calculating the membership value of each and every pixel. Then, the corrupted pixel subjected to the second stage where they are replaced by mean value of uncorrupted neighbouring pixels selected from a window adaptively. If the numbers of uncorrupted pixels in the selected window are 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 a result window size may vary pixel to pixel while filtering. Comparison shows the proposed filter effectively removes the impulse noise with significant image quality compared with conventional method such as the Standard Median Filter(SMF), Adaptive Median Filter(AMF), Progressive Switching Median Filter(PSMF) and recently proposed methods such as Efficient Decision Based Algorithm (EDBA), Improved Efficient Decision-Based Algorithm (IDBA) and fuzzy-based decision algorithm (FBDA). 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%. The efficiency of the proposed algorithm is evaluated using different standard images.

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1. 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 being the maximum and minimum intensities, 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 [1]. To get rid of such real world problem different methods have been proposed.

Emergent techniques based on Fuzzy Logic [2] 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, fuzzy techniques for image processing applications have mainly dealt with high-level computer vision and pattern recognition [3, 4].

In traditional median filtering [5] called standard median filter (SMF), the filtering operation is performed across to each pixel without considering whether its contamination status. So, the image details contributed by the corrupted 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 [6, 7], a noise detection mechanism has been incorporated so that only those pixels identified as corrupted would undergo the filtering process, while uncorrupted ones are kept intact. The progressive switching median filter (PSMF) [8] 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 manner in the second stage. In this method, impulse pixels located in the middle of large noise blotches can also be properly detected and filtered. This method shows better result up to 60% noise, but the performance drastically reduced beyond it due to use of fixed window size. Adaptive median filter (AMF) [9] is used for discriminating corrupted and uncorrupted pixels and then applies the filtering technique. Noisy pixels are replaced by the median value, and uncorrupted pixels are 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. This leads to degradation of fine details such as edges in filtered image for highly corrupted image, i.e. beyond 70% noise. A decision-based algorithm (DBA) [10] uses a fixed window size of 3×3, where the corrupted pixels are replaced by either the median pixel or neighbourhood pixels. It shows promising result with lower processing time which degrades the visual quality of the image as the noise density increased. To overcome this problem, an improved decision-based algorithm (IDBA) [11] 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. It can give the acceptable result up to 80% noise. The FBDA [12] is an improved fuzzy-based switching median filter in which the filtering is applied only to corrupted pixels in the image while the uncorrupted pixels are left unchanged. During the time of filtering process FBDA selects only uncorrupted pixels in the selected window based on a fuzzy distance membership value.It is observed that, most of the schemes proposed so far;

1. was a smaller window(3×3) at low density noise and larger window at high density impulse noise.
2. uses median fitting for uncorrupted pixels in a window.

But in a real time environment the density in percentage are not known apriori as the knowledge of original image is not available. Hence choosing a fixed size window in real time is an unrealistic assumption. Further, even at high density noise, choosing a larger size window for a pixel for which its smaller window contains sufficient uncorrupted pixel with lead to distortion in restored images. To achieve these objectives in this paper, we propose an adaptive fuzzy based mean filtering (FBAMF). Even though the detection of corrupted pixel is based on , the filter selects a window size adaptively based on the window corruption characteristics. Further, at higher noise density average filter performs better than the median filter [13], we apply average filter for corrupted pixel. The window size is allowed to grow maximum size 15×15 to reduce the distortion and computational complexity. Comparative analysis shows the superiority over the reported scheme.

The next of the paper is organized as follows. Section 2 outlines the noise model. The performance measures used are defined in section 3. The suggested algorithm is described in section 4. Simulation results and performance analysis is given in section 5. Finally, the section 6 deals with concluding remarks.

2. 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 mathematically expressed as ,

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

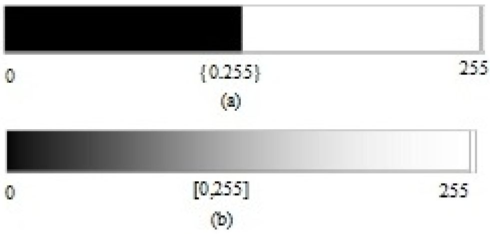

Figure 1: Representation of (a) Salt and Pepper Noise with $R_{i,j} \in \{0, 255\}$ (b) Random Valued Impulsive Noise with $R_{i,j} \in [0, 255]$

$x(i, j)$ denotes a noisy image pixel, $y(i, j)$ denotes a noise free image pixel and $\eta(i, j)$ denotes a impulse at the location (i, j). In salt and pepper noise, noisy pixels take either minimal or maximal values i.e. $\eta(i, j) \in \{0, 255\}$ and for random-valued impulse noise, noisy pixels take any value within the range minimal to maximal value i.e. $\eta_(i, j)$ $\in [0, 255]$. In this paper, we focus only on salt-and-pepper noise. Both the models are depicted in Fig 1.

3. PERFORMANCE MEASURES

The metrics used for performance comparison among different filters are defined below:

3.1. 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:

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

Where Mean Squared Error (MSE)is defined as:

$$MSE = \frac{1}{M \times N}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}(X_{ij} - \hat{X}_{ij})^2 \quad (3)$$

3.2. Image Quality Index(IQI)

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 [14], 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 [12, 14] can be defined as below:

$$IQI_j = Corr(X_w, \hat{X}_w) * Lum(X_w, \hat{X}_w) * Cont(X_w, \hat{X}_w) \quad (4)$$

where
$Corr(X_w, \hat{X}_w) = \sigma_{X\hat{X}}/\sigma_X\sigma_{\hat{X}}$
$Lum(X_w, \hat{X}_w) = 2\mu_X\mu_{\hat{X}}/(\mu_X^2 + \mu_{\hat{X}}^2)$
$Cont(X_w, \hat{X}_w) = 2\sigma_X\sigma_{\hat{X}}/(\sigma_X^2 + \sigma_{\hat{X}}^2)$

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. The statistical parameters μ_X,σ_X and $\mu_{\hat{X}}$,$\sigma_{\hat{X}}$ are mean and standard deviation of the X_w and $\hat{X}_w$respectively. Further, $\sigma_{X\hat{X}}$ is the co-variance of X_w and $\hat{X}_w$. Here, we have chosen $w = 8$. 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,

$$IQI = \frac{1}{M}\sum_j IQI_j \quad (5)$$

$$j = 1, 2....M$$

The dynamic range of IQI lies in the range of -1 to 1. The best value 1 is achieved if and only if restored image $\hat{X}$ is equal to the original image X.

4. PROPOSED METHOD

The proposed scheme FBAMF is a non-recursive filter works on two stages i.e. noise detection followed by application of adaptive mean filtering to the corrupted pixel only. The noise considered in this paper is only salt and pepper noise with uniform distribution.The filtering is applied only to the noisy pixels whereas the noise-free pixels retained their original value.

tb]

Algorithm FBAMFStep 1. Initialize a sub-window size, $w = 3$ and maximum window size,$w_{max} = 15$ Step 2. Select a sub-window 'W' of size $w \times w$ with center pixel as x_{ij} and defined as.

$$W = \left\{x_{i+r,j+s}|r, s \in \left(-\frac{w}{2}, \frac{w}{2}\right)\right\}$$

Step 3. If ($x_{ij} = 0$ or $x_{ij} \neq 255$), proceed to the next step, otherwise the pixel value is left unchanged. Step 4. Collect all the pixels in W as

$$W_s = \{s_{ij} = x_{ij} \in W|x_{ij} \notin \{0, 255\}\}$$

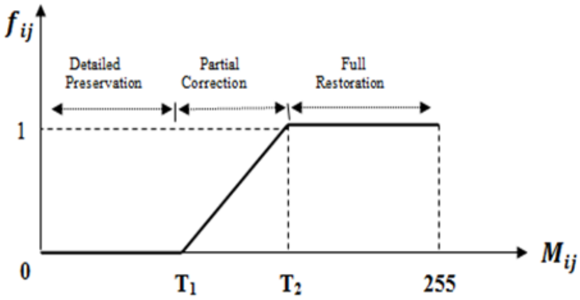

Figure 2: Fuzzy set used for noise detection

Step 5. If the size of $W_s \geq 0$,

1. Find $M_{ij} = max\{|x_{ij} - s_{ij}|, s_{ij} \in W\}$
2. Find Fuzzy measure(Membership function) of corruption at x_{ij} as

$$f_{ij} = \begin{cases} 0, \ M_{ij} \leq T_1 \\ \frac{M_{ij}-T_1}{T_2-T_1}, \ T_1 < M_{ij} < T_2 \\ 1, \ M_{ij} \geq T_2 \end{cases}$$

3. Replace the center pixel by
$y_{ij} = (1 - f_{ij}) * x_{ij} + f_{ij} * m_{ij}$
where,m_{ij} is the mean ofW_s.

Else Size(W) = Size(W) + 2
Step 6. If Size(W) $\leq w_{max}$, go to Step 4. Else replace the center pixel by mean of the pixels in sub-window of size w_{max}.
Step 7. Shift the window first row wise and then column wise until all the pixels in the image are processed.

end

4.1. Fuzzy Based Noise Detection Stage

The role of fuzzy noise detection is to generate a fuzzy flag map which gives each pixel a fuzzy flag indicating how much it like an impulse pixel.If the center (test) pixel x_{ij} in a 3×3 window W is either 0 or 255 it is considered to be noisy. The maximum value M_{ij} of the difference measure for each pixel in the selected window based on the current pixel x_{ij} can be calculated as follows:

$$M_{ij} = max\{|x_{ij} - s_{ij}|, s_{ij} \in W\} \qquad (6)$$

Fig:2 shows the fuzzy set used to give the pixel x_{ij} a membership function f_{ij} indicating how much it is corrupted, where M_{ij} is used as the fuzzy input variable and the two predefined thresholds T1 and T2 are set to 15 and 25 respectively [15].

4.2. Adaptive mean Noise Filtering:

Once a pixel identified as noisy then the linear combination between the current pixel and 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 in increased to 5×5 and the process is repeated till the window size reaches to a predefined maximum window size. The overall FBAMF steps followed are shown in Algorithm 1.

5. SIMULATION AND RESULT

To validate the proposed FBAMF, simulation has been performed on standard images, like Lena, Boat, and Peppers of size 512×512 as shown in Fig.3. 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, AMF, PSMF, DBA, IDBA, FBDA are applied to the noisy images. The simulation is carried out using MATLAB.The performance measures discussed above are used to prove the superiority of the proposed method. The performance parameter values such as PSNR and IQI obtained after applying the various filters are compared by varying the noise density from 10% to 90% are shown in Table-I and II respectively. From the quantitative values shown in the tables, it may be observed that FBAMF algorithm outperforms all other noise removal schemes.

The PSNR and IQI of the restored images obtained from different existing scheme mentioned above simulated along with the proposed method and plotted in Fig 4 and 5 for Boat image respectively. It has been observed that the proposed scheme at low as well as high noise density is superior to all other scheme.In addition to the IQI value and the image quality map has also been generated to evaluate the performance of the different algorithms as shown in Fig.6. Brighter image quality map (IQI ≈ 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.

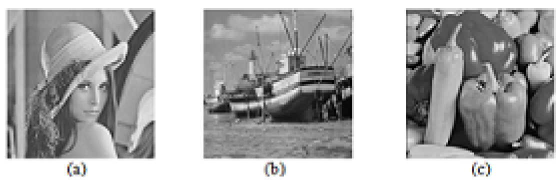

Figure 3: (a)Original Lena image (b) Original Boat image (c) Original Peppers image

Fig.6 show their stored image and the corresponding image quality map of various filter applied on noisy images of 30%, 60% and 90% noise density. It may be observed that the image quality map of the proposed method is brighter as compared to other for low as well as high density salt and pepper noise.

Table 1: Comparative analysis of PSNR for various filters in lena image

Noise(%)	SMF	PSMF	AMF	DBA	IDBA	FBDA	FBAMF
10	34.3624	36.8431	39.5265	39.0850	39.6600	39.8873	44.0265
20	29.5833	33.2382	34.8684	36.5952	36.8526	37.8334	40.5190
30	23.8910	30.9431	32.3878	34.2939	34.5395	36.1045	38.2436
40	19.0081	27.5024	30.2430	32.2594	32.6563	34.3641	36.4458
50	15.2828	26.2964	28.4616	30.3886	31.0516	33.0858	35.0063
60	12.2427	24.8570	26.8338	28.4584	29.3937	31.7549	33.3480
70	9.9588	20.9470	25.0211	26.3646	28.0187	30.0721	31.3843
80	8.1050	13.7021	23.2912	23.7943	25.9108	28.5338	29.5153
90	6.5740	7.7175	20.6217	20.1332	22.6076	26.6898	26.9148

Table 2: Comparative analysis of IQI for various filters in lena image

Noise(%)	SMF	PSMF	AMF	DBA	IDBA	FBDA	FBAMF
10	0.8789	0.9672	0.9427	0.9310	0.9338	0.9447	0.9736
20	0.8060	0.9488	0.9169	0.9205	0.9217	0.9385	0.9613
30	0.6211	0.9241	0.8838	0.8976	0.8977	0.9187	0.9461
40	0.3488	0.8936	0.8431	0.8627	0.8647	0.8917	0.9282
50	0.1645	0.8641	0.8001	0.8179	0.8258	0.8614	0.9062
60	0.0771	0.8175	0.7418	0.7570	0.7756	0.8222	0.8743
70	0.0404	0.7108	0.6736	0.6704	0.7177	0.7742	0.8322
80	0.0188	0.3618	0.5652	0.5395	0.6231	0.6689	0.7631
90	0.0081	0.0332	0.3916	0.3138	0.4327	0.5723	0.6347

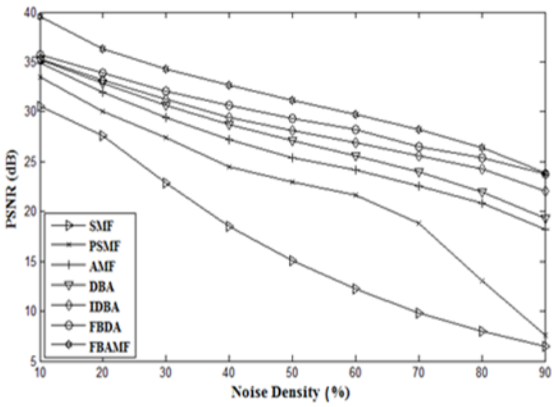

Figure 4: PSNR characteristics for Boat image at various noise densities

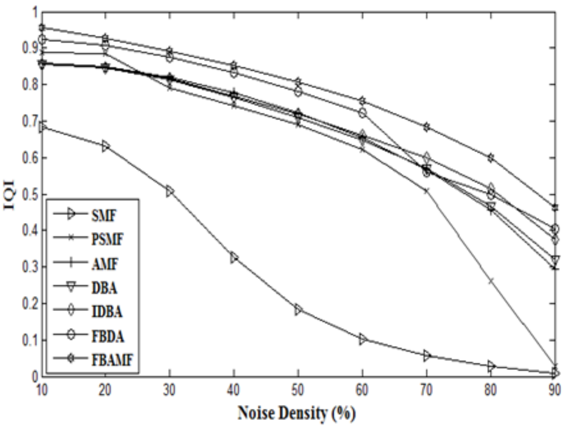

Figure 5: IQI characteristics for Boat image at various noise densities

To verify the effectiveness of the proposed method for very high density noise, experiment has been carried on images corrupted with 95% of salt and pepper noise. Fig.7 shows the result of various filters for salt-and-pepper image of 95% noise density. It may be observed that the quality of the restored image using proposed algorithm is better than that of the existing algorithms.

6. CONCLUSION

In this paper, we propose a fuzzy based adaptive mean filtering scheme, namely, FBAMF 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 identification of noisy pixels from a selected window is made based on a fuzzy decision. 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

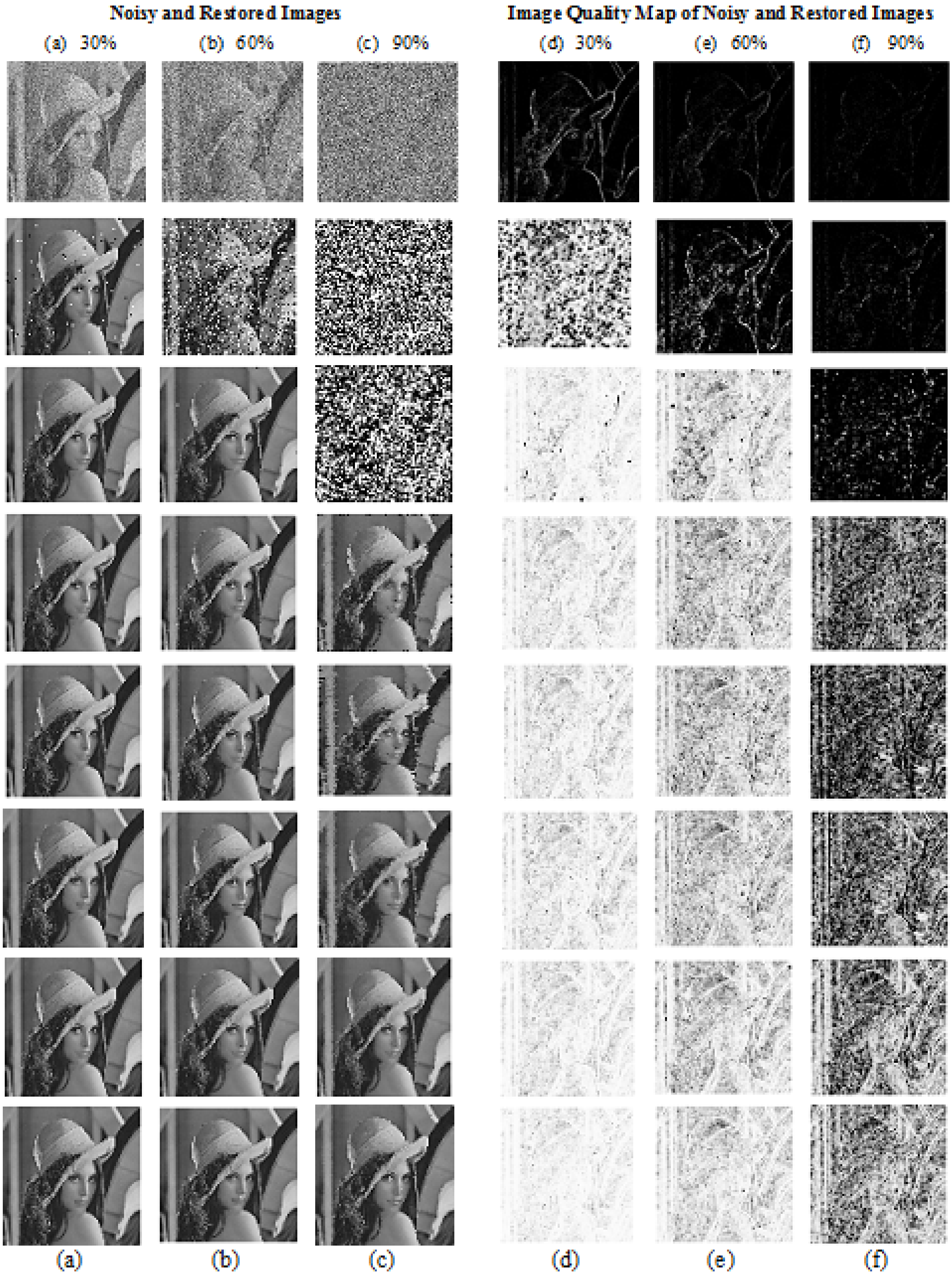

Figure 6: Column a, b and c represent the noisy and restored images of Lena image corrupted with 30%, 60% and 90% noise respectively. Lena image corrupted with 30%, 60% and 90% noise respectively. Column d, e and f represent the corresponding image quality map. Rows 1, 2, 3, 4, 5, 6, 7 and 8 represent the noisy images and the results of SMF, PSMF, AMF, DBA, IDBA, FBDA and FBAMF filters respectively.

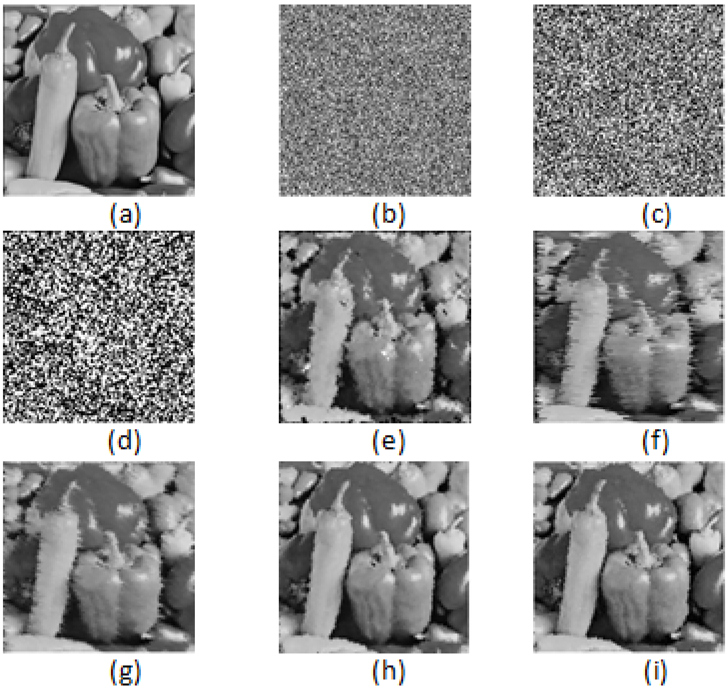

Figure 7: Results of various filters for peppers image corrupted by 95% noise densities. (a) Original peppers image. (b) Noisy Image(c) Output of SMF. (d) Output of PSMF. (e) Output of AMF. (f) Output of DBA. (g) Output of IDBA. (h) Output of FBDA (i) Output of FBAMF

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 images details at high densities impulse noise.

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