A Non-Linear Image Denoising Method for Salt-&-Pepper Noise Removal using Fuzzy-Based Approach

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Abstract— **The paper proposes an Improved Fuzzy-Based Decision Algorithm (IFBDA) for the restoration of images that are highly corrupted by Salt-and-Pepper noise. The new algorithm utilizes a modified version of the detection phase of FBDA to get better image quality than the existing algorithm. The proposed algorithm produces better result than the conventional and other advanced fuzzy-based non-linear filters. Different images have been tested by using the proposed algorithm (IFBDA) and found to produce better Peak-Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), Image Enhancement Factor (IEF) and Image Quality Index (IQI) values.**

Keywords- Fuzzy, Decision-based Algorithm, impulse noise, median filter, salt-and-pepper noise.

I. Introduction

Two common types of impulse noise are the salt-and-pepper noise and the random-valued noise. For images corrupted by salt-and-pepper noise, the noisy pixels can take only the maximum and the minimum values in the dynamic range. Thus, it could severely degrade the image quality and cause some loss of information. Various linear filters have been proposed in the literature for noise removal, but those have a drawback that they could produce serious image blurring even in low noise density [5]. Consequently, nonlinear filters have been widely exploited due to their much improved filtering performance in terms of impulse noise attenuation. The median filter was once the most popular nonlinear filter for removing impulse noise because of its good denoising power and computational efficiency [2] [7]. Due to its effectiveness in noise suppression and simplicity in implementation, various modifications of the SMF have been introduced, such as the weighted median (WM) [2] filter and the center weighted (CWM) [10] filter. The major drawback of the SMF is that the filter is effective only for low noise densities and additionally, exhibits blurring if the window size is large. This leads to insufficient noise suppression if the window size is small [14]. An intuitive solution to overcome this problem is to implement an impulse-noise detection mechanism prior to filtering. For this, switching median filters [4] [13] [17] [18] can be used, which gives significant performance improvement compared to any other existing advanced methods for impulse noise removal.

In switching median filters, 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. 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 since the corrupted pixels that are replaced by the median values are very few. The major drawback of this method is that defining a robust decision measure is difficult. These filters will not take into account the local features as a result of which edge details may not be recovered satisfactorily, especially when the noise is high.

Chan et al. [3] proposed an algorithm to overcome this problem, which consists of two stages. The first stage is to classify the corrupted and uncorrupted pixels by using AMF, and in the second stage, regularization method is applied to the corrupted pixels to preserve edges and suppress noise. The drawback of this method is that for high impulse noise, it requires large window size of 39 × 39 and additionally requires complex circuitry for the implementation and determination of smoothing factor β to get good results [3].

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Srinivasan and Ebenezer [16] proposed an efficient decision-based algorithm (EDBA) in which the corrupted pixels are replaced by either the median pixel or neighborhood pixel by using a fixed window size of 3 × 3 resulting in lower processing time and good edge preservation. Although EDBA filter [16] showed promising results, a smooth transition between the pixels is lost leading to degradation in the visual quality of the image in the form of line artifacts, since it only considers the left neighborhood from the last processed value. To overcome this problem Madhu et al. [11] [12] proposed an improved decision-based algorithm (IDBA) in which corrupted pixels can be replaced either by the median pixel or, by the mean of processed pixels in the neighborhood, which results in a smooth transition between the pixels with edge preservation and better visual quality. The drawback 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 neighborhood.

To address high noise density, a noise adaptive soft switching median (NASM) filter was proposed in [4], which consists of a three-level hierarchical soft-switching noise detection process. The NASM achieves a fairly robust performance in removing impulse noise, while preserving signal details across a wide range of noise densities. However, the quality of the recovered image becomes significantly degraded when noise density is greater than 50%. To overcome performance degradation at higher noise density, a new efficient method called BDND [13] has been introduced and it has shown better results. But at high noise density, BDND shows higher misdetection and false alarm rate (at random noise). Consequently, it could not preserve the edge details of the recovered image and the quality of the restored image is reduced. The main drawback of switching median filters like BDND is that in the case of high-density impulse noises, there is still a chance for good representation of the corrupted pixels in the selected window to take part in the filtering process, which may lead to the degradation of image quality.

Another drawback of BDND switching filter is that it first uses a window size of 21 × 21 to detect whether a pixel is corrupted or not and again a second iteration is performed on a reduced window size of 3 × 3 with same set of steps to reduce the misclassification of pixels. Actual filtering process begins after the two levels of iterations. Consequently, BDND algorithm consumes a lot of time.

In order to overcome the drawbacks of the above filters, Madhu et. al [17] proposed a new fuzzy-based decision algorithm (FBDA) for removing impulse noise at a wide range of noise densities, especially for high impulse noise. FBDA 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. What makes FBDA different from other switching median filters such as BDND is that during the time of filtering process FBDA selects only uncorrupted pixels in the selected window based on a fuzzy distance membership value. Thus, the advantage of FBDA is that it has both the noise detection power and the power of eliminating corrupted pixels during the filtering process. Another advantage of FBDA is that it uses only one level of iteration to detect whether a pixel is corrupted or not and it uses a fixed window size of 3 × 3 or 5 × 5 (based on the noise density) for both the noise detection and the filtering process. The drawback of FBDA is that it doesn't give better results for low noise densities because of the fact that the rule used for deciding whether a pixel is corrupted or not will misclassify certain pixels as noisy pixels. For high noise densities, the rule will correctly classify noisy pixels and the filtered results are very promising. In this work we have modified the noise detection rule to get an improved FBDA method (IFBDA) which works well in both low and high noise densities.

II. Proposed Algorithm (IFBDA)

In IFBDA, we calculate the variance measure for each pixel based on the neighborhood values. If the pixel is an uncorrupted pixel, then the variance measure value will be probably small and otherwise it will be probably high. In addition to this we also calculate the difference measure values for each pixel in the neighboring window and take the sum of all those values. If the pixel is an uncorrupted pixel, then the sum of the difference measure values will be probably less. Incorporating these two conditions, the noise detection rule for IFBDA can be modified to get better results. Let $C_{i,j}$ represent the central pixel under consideration and let $W_{\min}$ and $W_{\max}$ represent the minimum and maximum intensity values within a selected window around $C_{i,j}$. Let S represents the sum of the difference values of each pixel in the neighboring window and let V represents the variance measure of the window. Then, IFBDA decision rule can be written as follows:

If ($W_{\min} < C_{i,j} < W_{\max}$) OR ($S<T_1$ and $V<T_2$) then $C_{i,j}$ is an uncorrupted pixel and its value is left unchanged. Otherwise $C_{i,j}$ is a noisy pixel.

Where T_1 and T_2 are two thresholds whose values have been found out empirically as 50 and 20, respectively. These values are selected based on a fixed window size of 5×5.

After classifying the pixels into corrupted and non-corrupted, the FBDA filtering process [17] is applied only to the corrupted pixels. During the time of filtering process IFBDA selects only uncorrupted pixels in the selected window based on a fuzzy distance membership value. Thus the advantage of IFBDA is that it has both the noise detection power as well as the power of eliminating corrupted pixels during the filtering process. For a pixel identified as a corrupted pixel, IFBDA selects a window which consists of neighborhood pixels. It then computes the difference measure for each pixel in that selected window based on the central pixel (the corrupted pixel) and then calculates the membership value for each based on the highest difference. IFBDA eliminates those pixels from the window with very high (close to 1) and very low (close to 0) membership values, since they may represent the impulse noises. Median filter is then applied to the remaining pixels in the window to get the new pixel value for the current pixel position.

The efficiency of the proposed algorithm is tested using standard images after applying four different noise models. From experimental analysis, it has been found that improved FBDA (IFBDA) method gives better results for low noise densities compared to FBDA. It has also been proved through experimental analysis that IFBDA produces better results for low noise densities in terms of quantitative measures such as PSNR, SSIM, IEF and IQI.

III. Results and Discussion

Cameraman image of size 256×256 have been used to test the performance of the algorithm with dynamic range of values (0, 255). Images will be corrupted by salt-and-pepper noise at different noise densities, such as low noise (30%), medium noise (60%) and high noise (90%). Then the PA is applied to the corrupted image to remove the noise, yielding the restored image. The performance of the restoration process is quantified using Peak Signal-to-Noise Ratio (PSNR), Structured Similarity Index (SSIM), Image Enhancement Factor (IEF) and Image Quality Index (IQI) defined as follows.

$$PSNR = 10*\log 10\ (255^2/MSE)$$

$$MSE = \sum_{m,n} [O(m, n) - R(m, n)]^2 / (M*N)$$

$$SSIM = L(O, R)*C(O, R)*S(O, R)$$

$$L(O, R) = (2\mu_O\mu_R+C_1) / (\mu_O^2+\mu_R^2+C_1)$$

$$C(O, R) = (2\sigma_O\sigma_R+C_2) / (\sigma_O^2+\sigma_R^2+C_2)$$

$$S(O, R) = (\sigma_{OR}+C_3) / (\sigma_O\, \sigma_R+C_3)$$

$$C_1 = (K_1*G)^2,\ C_2 = (K_2*G)^2,\ C_3 = C_2/2$$

$$G = 255;\ K_1, K_2 << 1,\ (K_1=0.001,\ K_2=0.002)$$

$$IEF = (\textstyle\sum_{m,n} [P(m, n)-O(m, n)]^2) / (\sum_{m,n} [R(m, n)- O(m, n)]^2)$$

where, *O* is the original Image, *R* is the restored image, *P* is the corrupted image, MSE is the mean square error, $M\times N$ 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.

IQI is designed by modeling any image distortion as a combination of three factors: loss of correlation, luminance distortion, and contrast distortion. Thus IQI can be written as a product of three components as follows:

$$IQI_j = Corr(O_w, R_w)*Lum(O_w, R_w)*Cont(O_w, R_w)$$

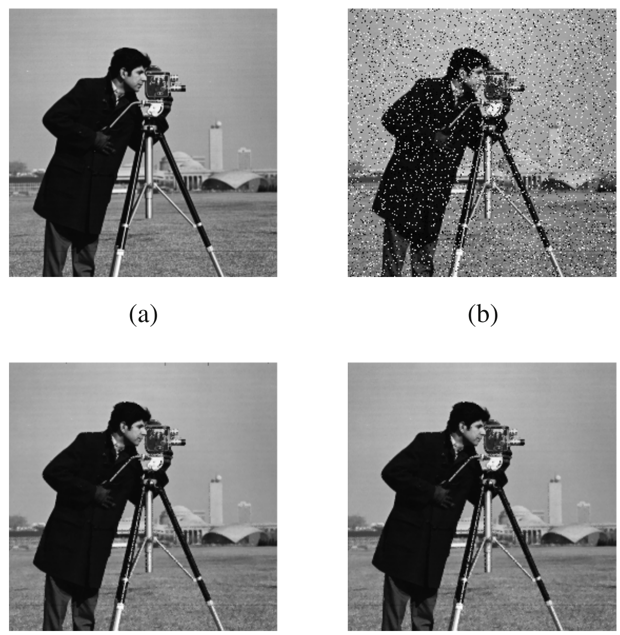
$$Corr(O_w, R_w) = \sigma_{OR} / (\sigma_O\sigma_R)$$

$$Lum(O_w, R_w) = (2\mu_O\mu_R)/ (\mu_O^2+\mu_R^2)$$

$$Cont(O_w, R_w) = (2\sigma_O\sigma_R) / (\sigma_O^2+\sigma_R^2)$$

IQI is first applied to local regions using a sliding window approach with size 8×8. At the jth step, the local quality index IQI_j is computed within the sliding window using the formula given above. O_w and R_w represents the sliding window of original and restored images respectively. If there are a total of M steps, then the overall image quality index is given by IQI = (1/M) Σ_j IQI_j, where j varies from 1 to M. The dynamic range of IQI is [-1, 1] and the best value 1 is achieved if the restored image R is equal to the original image O.

Table 1-12 shows the comparative performance analysis of FBDA and IFBDA in terms of quantitative measures like PSNR, SSIM and IEF, and in terms of qualitative measure like IQI. The quantitative values shown in the Tables1-4, 5-8 and 9-12 are obtained after applying the FBDA and IFBDA filters on corrupted cameraman, lena and circuit images, respectively. From the tables values, it is evident that the proposed IFBDA performs better compared to FBDA. Fig 1-3 (a), (b), (c) and (d) shows the original, corrupted and restored images after applying FBDA and IFBDA filters, respectively. From the visual results, it is evident that the proposed IFBDA filter produces promising output compared to IFBDA.



(a) (b) (c) (d)

Figure 1. (a) original cameraman image (b) cameraman image corrupted with 10% noise (c) Filtered image using FBDA (d) filtered image using IFBDA

TABLE I. PERFORMANCE ANALYSIS OF FBDA AND IFBDA IN TERMS OF PSNR FOR CORRUPTED CAMERAMAN IMAGE WITH LOW NOISE

Noise Level	FBDA	IFBDA
10%	30.61	30.71
20%	29.52	29.63
30%	28.41	28.53

TABLE II. PERFORMANCE ANALYSIS OF FBDA AND IFBDA IN TERMS OF SSIM FOR CORRUPTED CAMERAMAN IMAGE WITH LOW NOISE

Noise Level	FBDA	IFBDA
10%	0.9927	0.9938
20%	0.9906	0.9918
30%	0.9879	0.9881

TABLE III. PERFORMANCE ANALYSIS OF FBDA AND IFBDA IN TERMS OF IEF FOR CORRUPTED CAMERAMAN IMAGE WITH LOW NOISE

Noise Level	FBDA	IFBDA
10%	35.53	36.15
20%	56.27	57.19
30%	64.41	64.59

TABLE IV. PERFORMANCE ANALYSIS OF FBDA AND IFBDA IN TERMS OF IQI FOR CORRUPTED CAMERAMAN IMAGE WITH LOW NOISE

Noise Level	FBDA	IFBDA
10%	0.8262	0.8876
20%	0.8382	0.8597
30%	0.8275	0.8343

TABLE V. PERFORMANCE ANALYSIS OF FBDA AND IFBDA IN TERMS OF PSNR FOR CORRUPTED LENA IMAGE WITH LOW NOISE

Noise Level	FBDA	IFBDA
10%	38.31	39.71
20%	36.85	37.52
30%	35.77	36.45

TABLE VI. PERFORMANCE ANALYSIS OF FBDA AND IFBDA IN TERMS OF SSIM FOR CORRUPTED LENA IMAGE WITH LOW NOISE

Noise Level	FBDA	IFBDA
10%	0.9979	0.9982
20%	0.9971	0.9976
30%	0.9963	0.9969

TABLE VII. PERFORMANCE ANALYSIS OF FBDA AND IFBDA IN TERMS OF IEF FOR CORRUPTED LENA IMAGE WITH LOW NOISE

Noise Level	FBDA	IFBDA
10%	193.73	196.65
20%	277.35	289.42
30%	325.04	340.71

TABLE VIII. PERFORMANCE ANALYSIS OF FBDA AND IFBDA IN TERMS OF IQI FOR CORRUPTED LENA IMAGE WITH LOW NOISE

Noise Level	FBDA	IFBDA
10%	0.9649	0.9687
20%	0.9383	0.9412
30%	0.9102	0.9152

TABLE IX. PERFORMANCE ANALYSIS OF FBDA AND IFBDA IN TERMS OF PSNR FOR CORRUPTED CIRCUIT IMAGE WITH LOW NOISE

Noise Level	FBDA	IFBDA
10%	39.51	39.98
20%	38.47	39.02
30%	37.07	38.14

TABLE X. PERFORMANCE ANALYSIS OF FBDA AND IFBDA IN TERMS OF SSIM FOR CORRUPTED CIRCUIT IMAGE WITH LOW NOISE

Noise Level	FBDA	IFBDA
10%	0.9981	0.9984
20%	0.9978	0.9982
30%	0.9971	0.9976

TABLE XI. PERFORMANCE ANALYSIS OF FBDA AND IFBDA IN TERMS OF IEF FOR CORRUPTED CIRCUIT IMAGE WITH LOW NOISE

Noise Level	FBDA	IFBDA
10%	287.93	298.34
20%	365.86	406.37
30%	497.70	512.81

TABLE XII. PERFORMANCE ANALYSIS OF FBDA AND IFBDA IN TERMS OF IQI FOR CORRUPTED CIRCUIT IMAGE WITH LOW NOISE

Noise Level	FBDA	IFBDA
10%	0.9725	0.9753
20%	0.9616	0.9675
30%	0.9500	0.9587

IV. CONCLUSION

In this paper, an improved fuzzy-based algorithm is proposed which gives better performance in comparison with other advanced noise removal algorithms in terms of PSNR, SSIM, IEF and IQI. The performance of the algorithm has been tested at low, medium and high noise densities. Especially at low noise density levels IFBDA gives better results in comparison with FBDA and gives approximately same results at high noise densities.

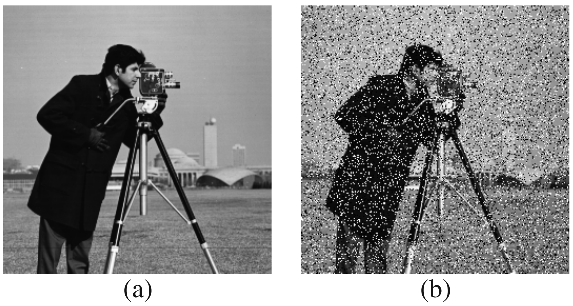


Figure 2. (a) original cameraman image (b) cameraman image corrupted with 20% noise (c) Filtered image using FBDA (d) filtered image using IFBDA

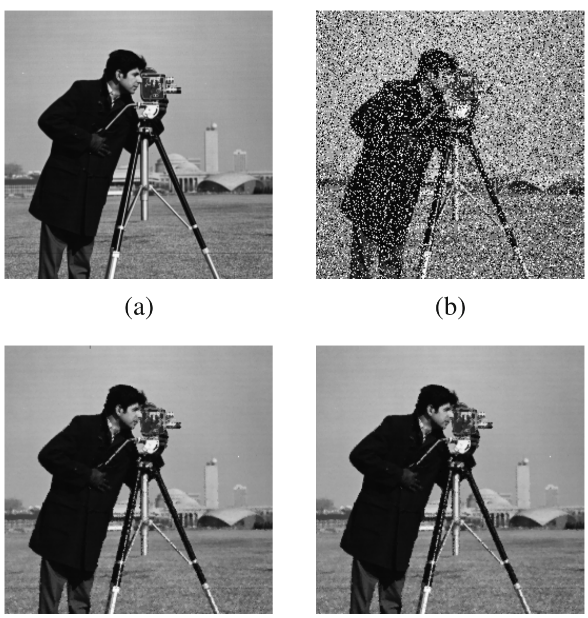


Figure 3. (a) original cameraman image (b) cameraman image corrupted with 30% noise (c) Filtered image using FBDA (d) filtered image using IFBDA

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