A Novel Fuzzy logic Based Impulse Noise Filtering Technique

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Abstract

A novel fuzzy logic based filtering technique is proposed to restore images corrupted by impulse noise. The proposed scheme is in two phases namely the detection of noisy pixels at all locations in the image using fuzzy knowledge based and application of recursive median filter on the corrupted pixels to remove the impulse noise. The performance of the proposed technique is tested on various test images corrupted at various noise densities and also compared with some of the existing filters. Experimental results show that the proposed technique exhibits superior performance than their counterparts and is efficiently capable of removing fixed-valued impulse noise densities, ranging from 5% to 40% in the image while at the same time effectively preserving the useful information in the image.

Keywords: *Impulse noise, Nonlinear filter, Fuzzy Logic, Defuzzification, Recursive median filtering, Peak Signal- to- noise Ratio.*

1. Introduction

Digital images are prone to impulse noise as a result of errors in the image acquisition or transmission process. Noise significantly degrades the image quality and cause great loss of information details in the image. It also complicates further image processing, such as image segmentation and edge detection.

Various filtering techniques have been proposed over the year, for removing impulse noise. It is well-known that linear filters could produce serious image blurring hence, nonlinear filters have been widely exploited due to their much improved filtering performance, in terms of impulse noise attenuation and edge/details preservation.

One of the most popular and robust nonlinear filters is the standard median (SM) filter [1], which exploits the rank-order information of pixel intensities within a filtering window and replaces the center pixel with the median value. However, the median filter tends to blur image details and remove thin lines even at low noise densities. To avoid the inherent drawbacks of the standard median filter, the weighted median filter [2] and the center-weighted median filter [3], which are modified median filters, have been introduced. These filters demonstrate better performance in preserving image. However, applying these filters unconditionally across the entire image without considering whether it is uncorrupted or corrupted as practiced in the conventional schemes would inevitably remove the uncorrupted detail pixels, destroy the image quality, and cause additional blur.

Many switching-based median filtering approaches for locating the distorted pixels prior to filtering have been suggested in the past by many researchers [4]-[9]. Although satisfactory results have been obtained in all these approach by incorporating noise detection mechanism into the filtering framework, however the study reveals that in case of uniformly distributed impulse noise, these techniques do not perform well as the noises are difficult to be detected and eliminated.

Considering the capability of neural network and fuzzy logic based processing, in recent years, many researches have been done on their applications in image noise detection/removal. Different methods for fuzzy based impulse noise removal have been proposed. In the work proposed by Zhang *et al.* [10], a fuzzy logic technique was used to detect and remove impulse noise. Their work was based on long-range correlation within different parts of the image. Schulte *et al.* [11], [12] proposed a fuzzy derivative estimation for noise detection and a fuzzy smoothing of neighboring pixels for noise removal. Lee *et al.* proposed a fuzzy image filter based on the genetic learning process [13]. These methods are vastly superior to the conventional methods hence they incur a very high computational cost.

In this paper a novel fuzzy logic based filtering scheme is proposed. The proposed scheme is simple but efficient and works alternatively in two phases: detection of noisy pixels followed by median filtering of the corrupted pixels to overcome many of the shortcomings observed in the existing methods. Detection operation is carried out at all locations but filtering is performed only at selected locations. The overall block diagram of the combined filter structure is depicted in Figure 1.

The outlined of the paper is as follows: Section II, reviews impulse noise model, Section III, presents the novel fuzzy impulse noise detection and removal scheme. Section IV, presents the experimental results, and Section V conclude the paper.

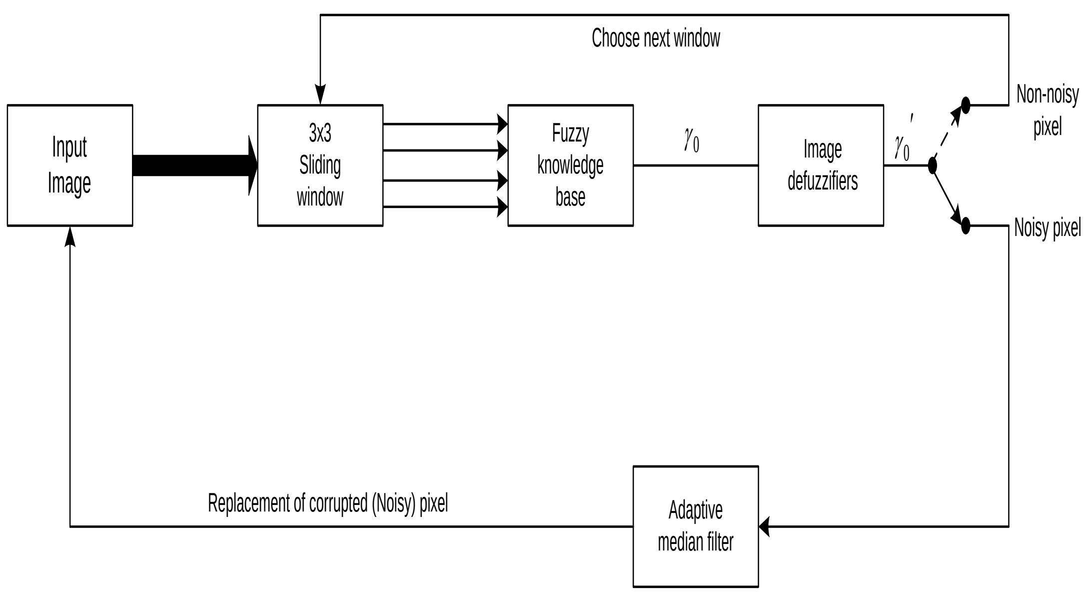


Fig. 1. Block Diagram of the Proposed Scheme

2. Impulse Noise Model

Impulsive noise is one such noise, which may affect images at the time of acquisition, transmission or storage. The image model containing impulse noise can be described as follows [14]:

$$X_{ij} = \begin{cases} N_{ij}, & \text{with } p \\ Y_{ij}, & \text{with } 1-p \end{cases} \tag{1}$$

where Y_{ij} and N_{ij} denotes the gray level of the original image and noise substituting for the original gray scale value at pixel location (i, j) respectively.

There are two cases of noise distributions for impulse noise: fixed valued impulse noise and random-valued impulse noise. For fixed-valued impulse noise which is also known as the "salt-and-pepper", values of the corrupted pixels are equal to $n_{\min}$ or $n_{\max}$ with equal probability [8]. For random-valued impulse noise, however, the corrupted pixel values are uniformly distributed between $n_{\min}$ and $n_{\max}$ [11]. For gray-level images with 8 bits per pixel (i.e., $n_{\min} = 0$ and $n_{\max} = 255$), the noise value N_{ij} of the first case corresponds to a fixed value of 0 or 255 with equal probability $(p/2)$, while that of the second case corresponds to a random value uniformly distributed in the range $[0, 255]$. In this paper, fixed-valued impulse noise was adopted as the noise model to test the system robustness.

3. Proposed Technique

A. Impulse Noise Detection and Fuzzy Rules

In this paper, at first for each pixel in the image the intensity difference between the center pixel and the neighboring pixels in a sliding window of 3×3 shown in Figure 2 is calculated. Since gray-scale images having intensity values in the range $[0, 255]$ are being considered, thus, the values is in the range $[-255, 255]$ and is denoted by,

$$D_i = abs(\mathrm{P}_i' - \mathrm{P}_0) \quad i = 1, \cdots, N^2 - 1 \tag{2}$$

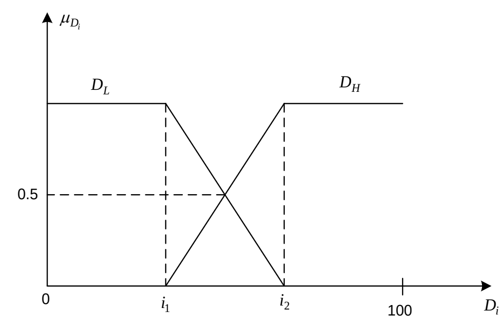
where $N = 3, 5, 7, \cdots$, depending on the window size.

By considering the intensity difference method and a fuzzy idea, four computed values are used to form a fuzzy knowledge base which in turn is used to detect whether a given pixel is noise or not. Many membership functions have been introduced in the literature. In the proposed scheme, trapezoidal membership functions are defined for the fuzzy system inputs. To applied this function, first D_i is mapped to the range of $[0\ 100]$. The mapped values are classified into two fuzzy partitions (regions) D_L and D_H as shown in Figure 3. The region, D_L constitutes the pixels that acquire low intensity difference value and the region, D_H constitutes the pixels that acquire high intensity difference value. To separate different D_i classes' two different thresholds i_1 and i_2 are used such that if D_i value is in the range of $[0\ \ i_2]$, the corresponding pixel is classified to D_L, and for the range of $[[i_1\ \ 100]$, the pixel is classified to D_H.

The output of fuzzy system explains to how extent a pixel could be noisy. By the defined fuzzy rules, the output γo variable has two fuzzy sets, φ_L and φ_H, where φ_L and φ_H correspond to pixel with low and high probability values belonging to non-noise and noisy pixel respectively. The membership functions corresponding to γo are shown in Figure 4. Sixteen fuzzy decision rules shown in Table 1 are used in the proposed fuzzy system.

P_1	P_2	P_3
P_4	P_0	P_5
P_6	P_7	P_8

Fig. 2. Applied Mask to Compute Intensity Different



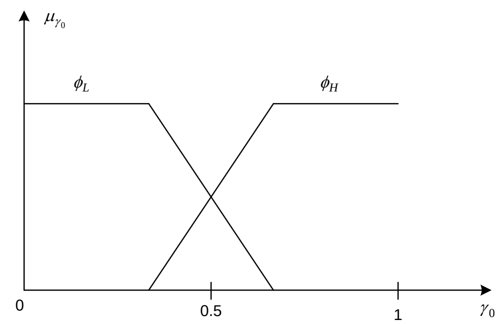


Fig. 3. Classes Membership Function **Fig. 4. Output Membership Function**

B. Defuzzification

The fuzzy sets output coming from the FKB are fed to the defuzzifier blocks. The defuzzifier defuzzifies the input fuzzy set and converts it into a single scalar value. Defuzzification is done using the following equation:

$$\gamma o_{Final} = \sum (\gamma o(j) \times C_j) \tag{3}$$

where $\gamma o(j)$ is the pixel membership value in $j'th$ class, and C_j is the output class center. γo_{Final} is the probability used for final pixel classification as noisy or non-noisy.

An optimum threshold level λ in the range of 0.6 to 0.95 is determined through experiments to binarize the output image produced through the defuzzifier i.e.,

$$\gamma o_{Final} = \begin{cases} 1, & \lambda \geq 0.6 \rightarrow 0.95 \\ 0, & \lambda < 0.6 \end{cases} \tag{4}$$

Thus, a pixel with probability greater than the threshold of 0.6 is classified as noisy while that with probability less than the threshold is not.

C. Recursive Median Filtering Algorithm

To process the corrupted image pixel, recursive median filter is applied. The two-dimensional median filter is realized by passing a $(2N+1)^2$ window over each point of the image signal, ranking the values in the window, and replacing each point with the output of the recursive median filter on that particular point before shifting the window to the next position. In image processing applications, it is necessary to apply the recursive median filter iteratively. By observing the functional optimization properties of recursive median filtering, the process of repeated applications of recursive median filtering is given by

$$\hat{Y}_i^{(t)}(k) = median\left\{\hat{Y}_i^{(t-1)}(k-N), \cdots, b_i(k), \cdots, \hat{Y}_i^{(t-1)}(k+N)\right\} \tag{5}$$

where the superscript t is the iteration index and $\hat{Y}_i^{(0)} = b_i(k)$.

This process can also be described by the following pseudo-C code. Here, we assume that the total number of signal points is L and at both ends of the signal, N points are appended to allow the filter to reach the edges of the signal.

```
Algorithm 1
Recursive-Median-Filter(){
  for(k = 1; k ≤ L; k++){Y_i(k) = b_i(k); }
  do {success = 0;
     for(k = 1; n ≤ L; k++){
     m = median{(Y_i(k − N), ···, b_i(k), ···, Y_i(k + N)}
     if (m == Y_i(k)) success++
     Y_i(k) = m;}}
  while(success ≠ L);}
```

That is, the original signal is used in the middle of the operation window throughout the whole process, instead of using the output of the previous pass. From the functional optimization properties of recursive median filtering, it can be easily understood that this operation has the properties of smoothing the signal and hence features such as thin lines and sharp edges can be better preserved.

4. Simulation Results

The proposed scheme in this paper is experimented upon to see how well it can remove the impulsive noises. The performance of the scheme as been examined on a variety of impulse noise-corrupted testing images corrupted with noise density ranging from 5% to 40%. The peak signal-to-noise ratio (PSNR) defined as

$$\text{PSNR} = 10\log_{10}\left(\frac{255^2}{\text{MSE}}\right) \tag{6}$$

is used as a quantitative performance indication, where MSE is the mean squared error, which is defined as

$$\text{MSE} = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\left[Y(i,j) - \hat{Y}(i,j)\right]^2 \tag{7}$$

where M and N are the total number of pixels in the horizontal and the vertical dimensions of the image. Y and $\hat{Y}$ denote the original and filtered image, respectively.

For comparison, the corrupted experimental images are subjected to filtering by the proposed schemes along with many other different standard methods namely standard median filters $\text{MF}(3\times 3)$, $\text{MF}(5\times 5)$, progressive switching median filter [7], Prescanned minmax center-weighted filters (PMCWF). All filtering schemes including the proposed scheme operate on a 3-by-3 sliding window.

The proposed method has been applied on variety of 512×512 test images which are shown in Fig. 5. Table 2 show the quantitative comparison of the proposed method and the existing methods with respect to images corrupted with fixed-valued impulse noise. The PSNR and MSE thus obtained with various noise levels are plotted in Fig. 6 and Fig. 7. From all the simulation results it could be observed that the proposed method exhibits much better performance than other methods in terms of PSNR and visual aspect. It is clearly seen that the proposed method successfully removes the noise from the image as well as at the same time efficiently preserves the useful image details.

5. Conclusion

A novel fuzzy logic based impulse noise detection and filtering technique is presented. The fundamental superiority of the proposed technique over most of the existing methods is it efficiency in detection of corrupted pixel and suppression of the detected impulse noise from digital images without distorting the useful information within the image. Extensive simulation experiments have been conducted on a variety of standard test images to demonstrate and compare the performance of the proposed method with many other well known techniques. As can be seen from the plots the proposed technique is far better than many other existing methods. The proposed technique is simple and easy to implement.

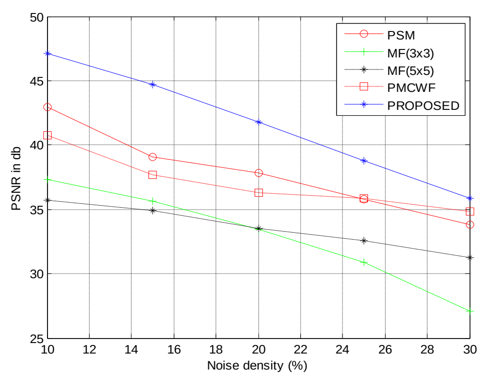


Fig. 6. PSNR Plot for Test Image 5(a) Corrupted with Different Noise Density

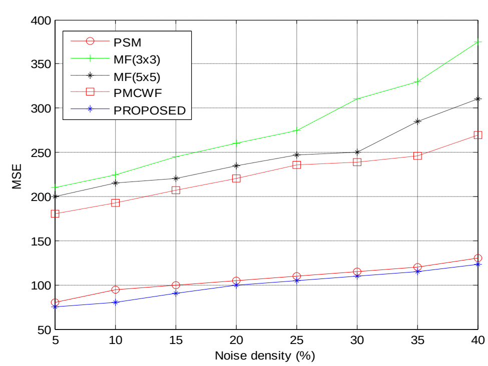


Fig.7. MSE Plot for Test Image 5(a) Corrupted with Different Noise Density

Table1: Fuzzy Rules

If $(D_1 \text{ is } lo)$ and $(D_2 \text{ is } lo)$ and $(D_3 \text{ is } lo)$ and $(D_4 \text{ is } lo)$ Then $(yo \text{ is } \varphi_L)$

If $(D_1 \text{ is } lo)$ and $(D_2 \text{ is } lo)$ and $(D_3 \text{ is } lo)$ and $(D_4 \text{ is } Hi)$ Then $(yo \text{ is } \varphi_H)$

If $(D_1 \text{ is } lo)$ and $(D_2 \text{ is } lo)$ and $(D_3 \text{ is } Hi)$ and $(D_4 \text{ is } lo)$ Then $(yo \text{ is } \varphi_H)$

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If $(D_1 \text{ is } lo)$ and $(D_2 \text{ is } Hi)$ and $(D_3 \text{ is } Hi)$ and $(D_4 \text{ is } lo)$ Then $(yo \text{ is } \varphi_H)$

If $(D_1 \text{ is } lo)$ and $(D_2 \text{ is } Hi)$ and $(D_3 \text{ is } Hi)$ and $(D_4 \text{ is } Hi)$ Then $(yo \text{ is } \varphi_H)$

If $(D_1 \text{ is } Hi)$ and $(D_2 \text{ is } lo)$ and $(D_3 \text{ is } lo)$ and $(D_4 \text{ is } lo)$ Then $(yo \text{ is } \varphi_H)$

If $(D_1 \text{ is } Hi)$ and $(D_2 \text{ is } lo)$ and $(D_3 \text{ is } lo)$ and $(D_4 \text{ is } Hi)$ Then $(yo \text{ is } \varphi_H)$

If $(D_1 \text{ is } Hi)$ and $(D_2 \text{ is } lo)$ and $(D_3 \text{ is } Hi)$ and $(D_4 \text{ is } lo)$ Then $(yo \text{ is } \varphi_H)$

If $(D_1 \text{ is } Hi)$ and $(D_2 \text{ is } lo)$ and $(D_3 \text{ is } Hi)$ and $(D_4 \text{ is } Hi)$ Then $(yo \text{ is } \varphi_H)$

If $(D_1 \text{ is } Hi)$ and $(D_2 \text{ is } Hi)$ and $(D_3 \text{ is } lo)$ and $(D_4 \text{ is } lo)$ Then $(yo \text{ is } \varphi_H)$

If $(D_1 \text{ is } Hi)$ and $(D_2 \text{ is } Hi)$ and $(D_3 \text{ is } lo)$ and $(D_4 \text{ is } Hi)$ Then $(yo \text{ is } \varphi_H)$

If $(D_1 \text{ is } Hi)$ and $(D_2 \text{ is } Hi)$ and $(D_3 \text{ is } Hi)$ and $(D_4 \text{ is } lo)$ Then $(yo \text{ is } \varphi_H)$

If $(D_1 \text{ is } Hi)$ and $(D_2 \text{ is } Hi)$ and $(D_3 \text{ is } Hi)$ and $(D_4 \text{ is } Hi)$ Then $(yo \text{ is } \varphi_H)$

Table2: Comparative Results in PSNR of Different Algorithms Applied to Test Image Figure 5(a) Corrupted by Various Rates of Fixed-Valued Impulse Noise

Filters	10%	15%	20%	25%	30%
MF (3 × 3)	35.98	35.00	33.57	32.51	31.56
MF (5× 5)	37.32	36.03	33.57	32.50	27.01
PMCWF	40.96	37.06	36.32	36.01	34.98
PSM	43.02	38.05	37.73	36.01	33.96
Proposed	47.03	44.93	42.31	38.86	36.01

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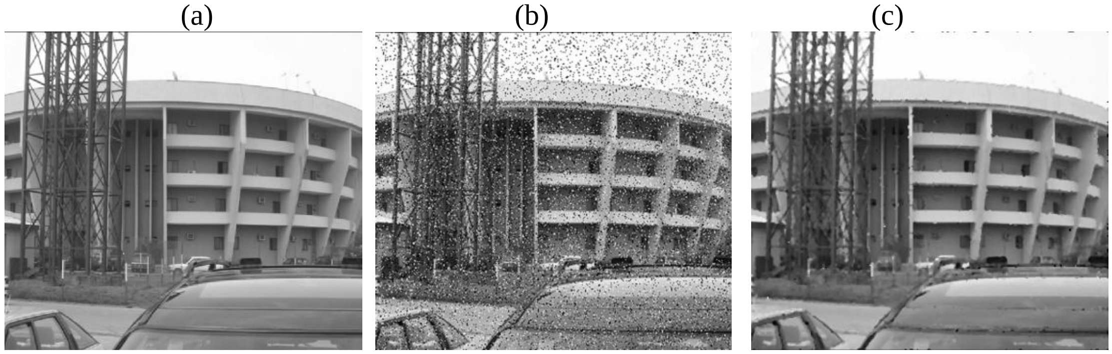
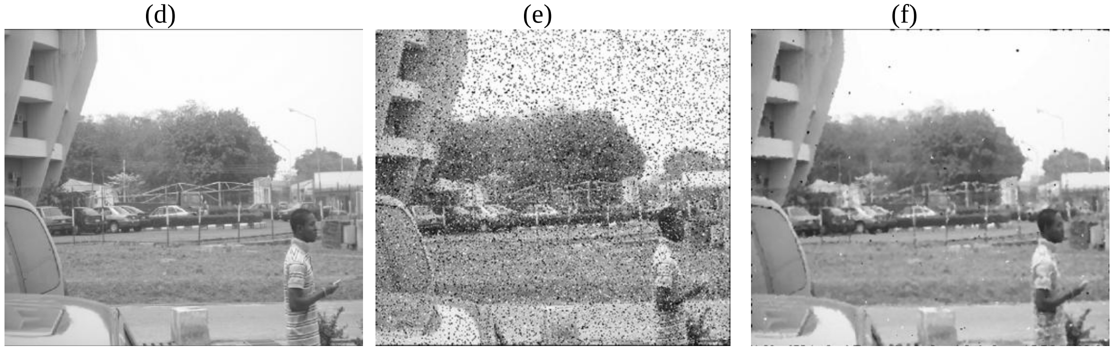
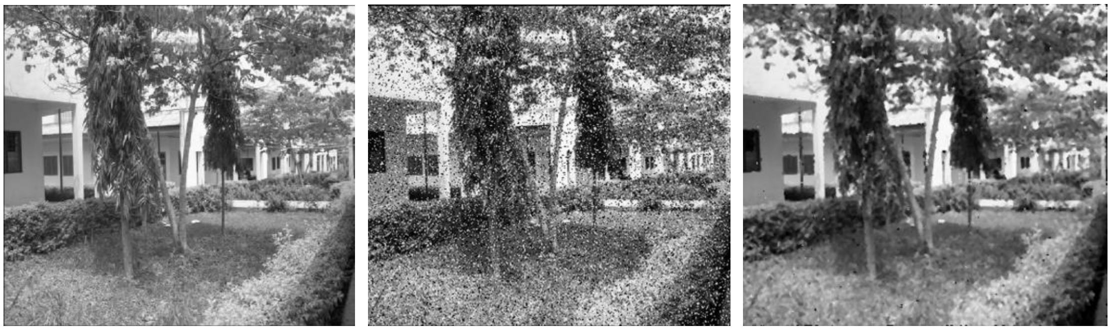
(a) (b) (c)



(d) (e) (f)



(g) (h) (i)



(j) (k) (l)

Figure 5: Test Images (a), (d), (g), (j) and corresponding noisy image corrupted by 10%,15%, 20%, and 25% fixed value impulse noise (b), (e), (h), and (k) respectively and (c), (f), (i), (l) are filtered image of (b),(e),(h), and (k) respectively.

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