

An Enhanced Mixed Noise Removal Technique for Color Images Using Fuzzy LogicJayasree M¹, V. Kabeer², N. K Narayanan³¹Computer Science and Engineering Department, Government Engineering College, Thrissur, Kerala, Indiamjayasree.arun@gmail.com²Department of Computer Science, Farook College, Calicut, Kerala, Indiavkabeer@gmail.com³School of Information Science and Technology, Kannur University, Kerala, Indianknarayanan@gmail.com

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ABSTRACT

Removing mixed noise from digital images is a challenging problem as it involves processing of various types of noise. Additionally, noises should be differentiated from inherent image structures. Fuzzy logic is a successful solution in this situation. In this paper, we propose a novel fuzzy technique to reduce mixed Impulse- Gaussian noise from color images. A weighted averaging process is used in this regard. The weights are computed using a fuzzy rule system which operates on an improved certainty function. This method performs effectively in reducing both the noise types and in preserving image details. The simulation experiments demonstrated that the method outperforms state-of-the-art filter.

Key words: Mixed noise, Fuzzy logic, Impulse-Gaussian noise, Certainty function.

INTRODUCTION

Mixed noises corrupt digital images to a larger level compared to individual noises, hence its removal is a tedious task. Gaussian noise may get added while capturing the image, which may be further contaminated by salt-and-pepper noise during transmission or storage. It is possible to reduce each type of noise separately, but, this process would reduce the computational efficiency, which makes it unsuitable for real time applications. Also, noises should be differentiated from the original image details such as edges. So, specific filters have to be devised which effectively removes mixed noise, at the same time preserves image details.

Various filtering techniques for removing mixed Gaussian-impulse noise have been studied in the literature. Filtering impulse noises individually from color images is a widely explored area [1], [2], [3], but only a few methods have been reported to handle mixed noises. A Peer group averaging (PGA) technique discussed by Deng et al., Hewer et al. Ho and Kenney et al. [4], [5], [6], [7] have been utilized in the fuzzy method by Morillas [8], in which a combination of a statistical method and an averaging operation is used to reduce Gaussian

noise. Studies on filtering techniques using Fisher linear discriminant [4], [5], [7], region analysis technique [6] and fuzzy algorithms [8] have been conducted. The trilateral filtering technique [9] which is based on the well known bilateral filter [11], [10] has been used to remove Gaussian noise. One of the techniques to remove salt-and-pepper noise uses a switching method for the filtering operation [12]. A weighted averaging method has been utilised in the adaptive nearest neighbor filter [13], [14] which handles impulse noise. Various partition based filters [15], [16] classifies each pixel to different signal activity groups. A Bayesian classification technique which utilises kernel regression was introduced in [18].

Mendiola-Santibañez, Jorge D. et al proposed a method for filtering mixed Impulse- Gaussian noise using morphological contrast detectors [17]. This method detects noise in two ways: By utilizing a contrast measure and by applying proximity criteria to various proposed toggle mappings.

Among the methods reported on filtering of mixed noises from color images, the filtering technique proposed by Joan-Gerard Camarena et al. is an outstanding one. In this method, a weighted

averaging filter operation is performed, by utilizing a fuzzy rule system [19]. The certainty degree equivalent to the similarity can be modified after studying the effect of different empirical formulas. The formula which showed excellent noise removal results have been adopted in this research work for color image filtering. In this paper, we propose an efficient noise removal algorithm that restores digital color images corrupted by mixed Impulse-Gaussian noise, using an improved certainty function.

The rest of the paper is organized as follows. Section II describes the Simple Fuzzy Rule Filter (SFRF) proposed by Joan-Gerard Camarena et al. Section III details the modified Certainty Degree for the proposed filter. Quantitative results presented in Section IV illustrate and compares the proposed filtering technique with SFRF filter. Finally, conclusions are presented in Section V.

II. SIMPLE FUZZY RULE FILTER (SFRF)

This filtering technique proposed by Joan-Gerard Camarena et al. is applied to RGB color images [19]. We shall represent the color image to be filtered as F , and a sliding filtering window of size 3×3 as W . The pixels within this window are represented as F_{ij} , where i and j varies from 1 to 3. The window is placed over the image in such a manner that the pixel to be filtered takes the central position in the window. As per our notation, this pixel is F_{22} . The vectors corresponding to the Red (R), Green (G), Blue (B) components in F are represented as

$$(F_{ij} = (F_{ij}^R, F_{ij}^G, F_{ij}^B).$$

A simple weighted averaging operation is used to perform the filtering task. The SFRF filtering algorithm consists of 4 steps [19]: 1) Finding the noisiness of each pixel 2) Finding the similarity between the pixel under processing and the remaining pixels in the window 3) Calculation of certainty degree for similarity 4) Computation of weights, using a fuzzy system. Through experimental study, it has been observed that by introducing an improved certainty function, the performance of the filter can be further enhanced. The modified certainty degree calculation is detailed in section IV

A. NOISINESS OF PIXELS

Consider another sliding window W' , of the same size as W , centered at F_{ij} . The elements in W' are denoted by F_{pq} , where p and q also varies from 1 to 3. Initially, we need to calculate how much noisy each pixel in the window W is. For this purpose, we define a new metric called distance measure, L , which is given below [19].

$$L(F_{ij}, F_{pq}) = \max \{ |F_{ij}^R - F_{pq}^R|, |F_{ij}^G - F_{pq}^G|, |F_{ij}^B - F_{pq}^B| \} \quad (1)$$

The values of i and j remains the same for each window W' , while the values of p and q varies from 1 to 3. This concept of windows W and W' is illustrated in Figure. 1.

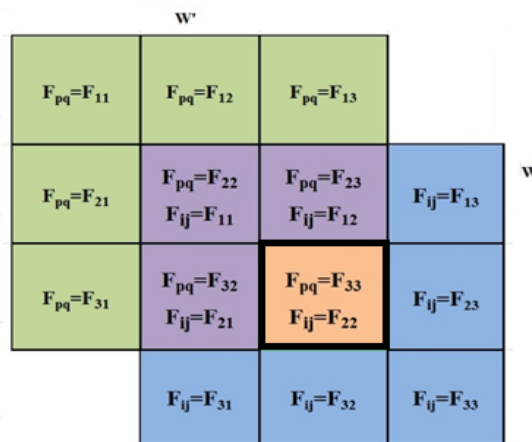


Figure1: Visualization of windows W and W'

Now, the pixels in W' are arranged according to ascending order of L . Then, the first $s+1$ pixels in W' are considered to compute the Rank Ordered Differences statistic (RODs) for F_{ij} [9], which is given as follows.

$$RODs(F_{ij}) = \sum_{1 \leq p,q \leq 3} L^t(F_{ij}, F_{pq}) \quad (2)$$

$1 \leq t \leq s+1$

Here, t is a variable used to keep track of the first $s+1$ RODs values, where the maximum value of t is $s+1$, so that the distance measure of the first $s+1$ pixels in the window W' is summed. $L^t(F_{ij}, F_{pq})$ represents the t^{th} value of the distance measure L . The setting of the parameter s is detailed in section IV.B. If the value of RODs (F_{ij}) falls within a small range, we can infer that the $s+1$ pixels in W' do not vary much from F_{ij} , so F_{ij} is probably noise free. Higher RODs (F_{ij}) value shows a higher degree of noise for F_{ij} .

Let $x = RODs(F_{ij})$. The certainty degree corresponding to the vague statement ' F_{ij} is noisy' can be represented as $\delta(F_{ij})$ and is defined as follows.

$$\delta(F_{ij}) = \begin{cases} 0, & x \leq k_1 \\ \frac{x-k_1}{k_2-k_1}, & k_1 < x < k_2 \\ 1, & k_2 \leq x \end{cases} \quad (3)$$

where the parameters k_1 and k_2 will be detailed in Section IV.B. A linear membership functions to decrease the time complexity. Every pixel F_{ij} that are not noisy is assigned a certainty degree using the fuzzy involutive operator, $1 - \delta(F_{ij})$. Figure 2.

Shows the certainty degrees corresponding to Rods(F_{ij})

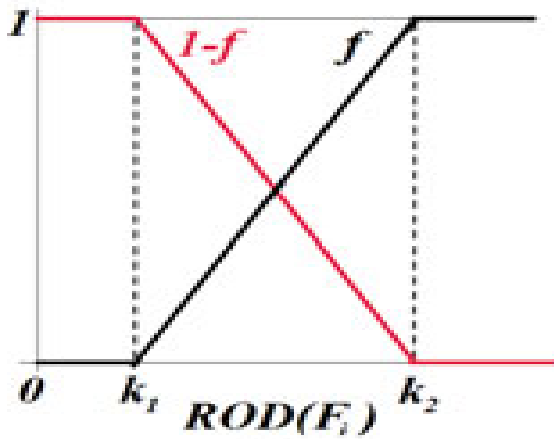


Figure 2: Certainty Degree of RODs

B. SIMILARITY COMPUTATION

To find the similarity between the pixel under processing F_{22} and the remaining pixels in the sliding window W , a new metric L' is used, which is called the similarity metric and is given below.

$$L'(F_{22}, F_{ij}) = |F_{22}^R - F_{ij}^R| + |F_{22}^G - F_{ij}^G| + |F_{22}^B - F_{ij}^B| \quad (4)$$

The L' metric measures the similarity better than L since its computation considers all the three components (R,G and B) of the pixels under comparison.

Utilizing the observed similarities, a certainty degree is assigned to the selected pixels of W , represented by F^{ij} , corresponding to the vague statements, similarity between F^{ij} and F_{22} is “low”, “medium” or “high” denoted by $\mu_L(F_{22}, F^{ij})$, $\mu_M(F_{22}, F^{ij})$, and $\mu_H(F_{22}, F^{ij})$, respectively. Now, pixels that would participate in the filtering operation need to be selected. Using the metric $L'(F_{22}, F_{ij})$, which is the distance between each pixel F_{ij} of the window W and F_{22} , the pixel under processing, a new arrangement is introduced to the nine pixels of W according to ascending order of the L' metric, and the first $m+1$ pixels are selected to perform the filtering operation, and are denoted as F^{ij} [19]. This selection is made, to avoid involvement of pixels entirely different from F_{22} in the filtering process. The setting of the parameter m is discussed in IV.B.

The certainty degree for the high, medium and low similarities has been computed using the following equations, where $x=L'(F_{22}, F^{ij})$.

$$\mu_H(x) = \begin{cases} 1, & x \leq a \\ -\frac{x}{(3a)} + \frac{4}{3}, & a < x < 4a \\ 0, & 4a \leq x \end{cases} \quad (5)$$

$$\mu_M(x) = \begin{cases} \frac{(x-a)}{a}, & a < x < 2a \\ 1, & 2a \leq x \leq 3a \\ \frac{(4a-x)}{a}, & 3a < x < 4a \\ 0, & \text{elsewhere} \end{cases} \quad (6)$$

Using the negation rule of fuzzy logic, we can compute μ_L as follows.

$$\mu_L(F_{22}, F^{ij}) = 1 - \mu_H(F_{22}, F^{ij}) \quad (7)$$

III. CERTAINTY DEGREE OF THE PROPOSED FILTER

In this paper, we propose a new method for calculation of certainty degree for medium similarity. After analyzing the effect of a range of empirical formulas for certainty degree, the empirical formula which showed excellent noise removal capability has been adopted for the proposed filter and is introduced in the equation below.

$$\mu_M(x) = \begin{cases} \frac{(2x-a)}{a}, & a < x < 2a \\ 1, & 2a \leq x \leq 3a \\ \frac{4a-x}{a}, & 3a < x < 4a \\ 0, & \text{elsewhere} \end{cases} \quad (8)$$

Figure.3 shows the modified certainty degree introduced corresponding to medium similarity, for the proposed filter

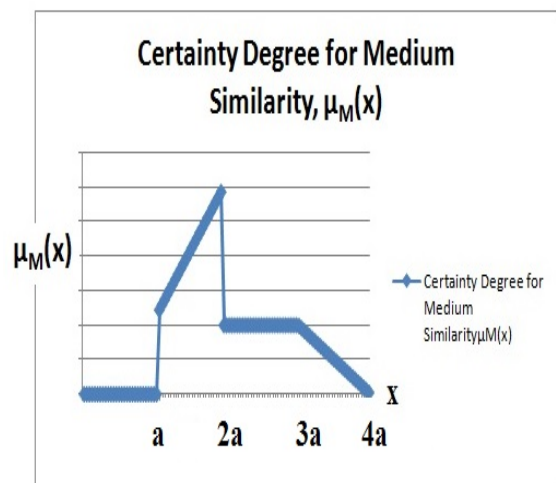


Figure 3: Certainty Degree of Medium Similarity for the proposed filter

IV. COMPUTATION OF WEIGHTS USING FUZZY SYSTEM

Rule-based fuzzy inference system is used to calculate the weights used in the filtering process as small, medium, or large. Finally, the defuzzification process calculates the value for each weight.

A. FUZZY RULES

The fuzzy rules are based on two core ideas: 1) Noisy pixels must be assigned a lower weight; and 2) Noise free pixels can be assigned a larger weight. This idea is elaborated in the following three fuzzy rules.

- 1) IF (F^{ij} is not noisy AND similarity between F_{22} and F^{ij} is medium AND F_{22} is noisy) THEN w_i is a medium weight.
- 2) IF (F^{ij} is not noisy AND similarity between F_{22} is low AND F_{22} is noisy) OR (F^{ij} is not noisy AND similarity between F^{ij} and F_{22} is high AND F_{22} is not noisy) THEN w_{ij} is a large weight.
- 3) IF (F^{ij} is noisy) OR (F^{ij} is not noisy AND similarity between F^{ij} and F_{22} is high AND F_{22} is noisy) OR (F^{ij} is not noisy AND similarity between F^{ij} and F_{22} is medium AND F_{22} is not noisy) OR (F^{ij} is not noisy AND similarity between F^{ij} and F_{22} is low AND F_{22} is not noisy) THEN w_{ij} is a small weight.

Prior to applying the fuzzy inference process, the fuzzy sets corresponding to the consequents of the fuzzy rules need to be defined. A certainty degree is associated with large, medium and small weight, $w_{ij} \in [0, 1]$, denoted by $v_L(w_{ij})$, $v_M(w_{ij})$, and $v_S(w_{ij})$, respectively. Figure .4. represents the fuzzy sets v_L , v_M , and v_S , where a triangular-shaped fuzzy membership function is selected for ease of the defuzzification step, as follows:

$$v_M(w_{ij}) = \begin{cases} \frac{(2w_{ij}-1)}{2b-1} + 1, & 1-b < w_{ij} \leq 0.5 \\ \frac{(1-2w_{ij})}{2b-1} + 1 & 0.5 < w_{ij} < b \\ 0, & \text{elsewhere} \end{cases} \quad (9)$$

$$v_L(w_{ij}) = \begin{cases} \frac{(w_{ij}-1)}{(1-b)} + 1, & b < w_{ij} \leq 1 \\ 0, & \text{elsewhere} \end{cases} \quad (10)$$

$$v_S(w_{ij}) = \begin{cases} \frac{w_{ij}}{(b-1)} + 1, & 0 \leq w_{ij} \leq 1-b \\ 0, & \text{elsewhere} \end{cases} \quad (11)$$

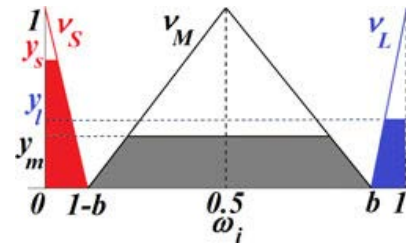


Figure 4: Fuzzy sets v_L , v_M , and v_S [19]

The value of the parameter b is set experimentally by trial and error method, and is detailed in section IV.A. The disjunction operation OR and the conjunction operation AND are applied to calculate the certainty degree of the antecedents of the fuzzy rules, by means of a t-norm $*$ and its associated s-norm $*$ '. The usual product is used as the t-norm and the probabilistic addition is used as the s-norm.

The consequents are assigned certainties corresponding to their antecedents, and finally, by defuzzification, weight w_{ij} of the pixel F^{ij} is obtained. The popular center of gravity (COG) technique is used for defuzzification [21], [22], [23] and is detailed below.

Let y_m , y_l , and y_s be the certainty degrees of the consequents in rules 1, 2, and 3 respectively for a pixel F^{ij} . In Fig. 3, considering the surface in each of the triangles and area under each of the three constant functions $y = y_m$, $y = y_l$ and $y = y_s$, three trapeziums are built. The polygonal line that is formed by the sides and tops of these trapeziums makes a fuzzy set A on $[0, 1]$, which is integrable in the conventional sense. The abscissa of COG for the area under A is the weight w_{ij} .

$$\text{Therefore, } \omega_i = \left(\int_0^1 x \cdot A(x) dx / \int_0^1 A(x) dx \right) \quad (12)$$

Finally, the filtering of the pixel under processing, F_{22} is performed by applying a weighted averaging operation on the m selected pixels in W , which is given below [19].

$$\left(\widehat{F}_{22} = \frac{\left(\sum_{\substack{1 \leq i, j \leq 3 \\ 1 \leq n \leq m+1}} w_{ij}^n F^{ij} \right)}{\left(\sum_{\substack{1 \leq i, j \leq 3 \\ 1 \leq n \leq m+1}} w_{ij}^n \right)} \right) \quad (13)$$

\widehat{F}_{22} is the pixel value of F after filtering. The weight w_{ij} lies between 0 and 1, which indicates the adaptivity of the method. The weights are different for each filtering window and are based on the local features, which enables processing of both noisy pixels and original image

pixels. The variable n is used to keep track of the number of times the weighted averaging operation needs to be performed, the maximum limit of which is $m+1$.

The weights w_{ij} of the first m pixels F^{ij} enable us to apply (13) to acquire the required denoised pixel \bar{F}_{22} . Algorithm of the proposed color image filter is given in Algorithm 1.

Algorithm 1: Proposed Color Image Filter

1. Read the color image F . The Vectors in F are $F_{ij} = (F_{ij}^R, F_{ij}^G, F_{ij}^B)$

2. The following steps are used to compute the noisiness of pixel F_{ij}

2.1 Define a window W centered at F_{22} . For each pixel

F_{ij} in the window W , define another window W' of same size 3×3 , centered at F_{ij} and represented as F_{pq} , p and q varying from 1 to 3.

Distance Measure,

$$L(F_{ij}, F_{pq}) = \max \{ |F_{ij}^R - F_{pq}^R|, |F_{ij}^G - F_{pq}^G|, |F_{ij}^B - F_{pq}^B| \}$$

2.2 Arrange the pixels in W' in ascending order of Distance Measure

2.3 For the first $s+1$ pixels, (ROD_s) is given by $ROD_s(F_{ij}) = \sum_{p=1, q=1}^{s+1} L(F_{ij}, F_{pq})$

For lower value of $ROD_s(F_{ij})$ Conclude F_{ij} is noise free. For higher values, Conclude F_{ij} is noisy.

2.4 Let $x = ROD_s(F_{ij})$, the certainty degree $\delta(F_{ij})$ of noisy pixels is defined by

$$\delta(F_{ij}) = \begin{cases} 0, & x \leq k_1 \\ \frac{x-k_1}{k_2-k_1}, & k_1 < x < k_2 \\ 1, & k_2 \leq x \end{cases}$$

Certainty Degree for pixels that are not noisy is defined as $1 - \delta(F_{ij})$

3. The following steps are used to compute the Similarity of pixels

3.1 Arrange the nine pixels of W according to ascending order of the L' metric

3.2 The first $m+1$ pixels are selected to perform the filtering operation, denoted as F_{ij}

3.3 Compute certainty degrees of High and Medium and Low similarities as μ_H, μ_M and μ_L

$$3.3.1 \mu_H(x) = \begin{cases} 1, & x \leq a \\ -\frac{x}{(2a)} + \frac{4}{a}, & a < x < 4a \\ 0, & 4a \leq x \end{cases}$$

$$3.3.2 \mu_M(x) = \begin{cases} \frac{(2x-a)}{a}, & a < x < 2a \\ 1, & 2a \leq x \leq 3a \\ \frac{4a-x}{a}, & 3a < x < 4a \\ 0, & \text{elsewhere} \end{cases}$$

3.3.3 Using the fuzzy negation, assign $\mu_L(F_{22}, F^{ij}) = 1 - \mu_H(F_{22}, F^{ij})$

4 This step Computes Weights using Fuzzy System.

The fuzzy rules are given by the following steps.

4.1 IF (F^{ij} is not noisy AND F_{22} is noisy AND the similarity between F_{22} and F^{ij} is medium) THEN w_{ij} is a medium weight.

4.2 IF (F^{ij} is not noisy AND F_{22} is noisy AND the similarity between F_{22} and F^{ij} is low) OR (F^{ij} is not noisy AND F_{22} is not noisy AND the similarity between F^{ij} and F_{22} is high) THEN w_{ij} is a large weight.

4.3 IF (F^{ij} is noisy) OR (F^{ij} is not noisy AND F_{22} is noisy AND the similarity between F^{ij} and F_{22} is high) OR (F^{ij} is not noisy AND F_{22} is not noisy AND the similarity between F^{ij} and F_{22} is medium) OR (F^{ij} is not noisy AND F_{22} is not noisy AND the similarity between F^{ij} and F_{22} is low) THEN w_{ij} is a small weight.

5 The triangular-shaped fuzzy membership functions corresponding to low, medium and high weights are given by v_L, v_M , and v_S

$$5.1 v_M(w_{ij}) = \begin{cases} \frac{(2w_{ij}-1)}{2b-1} + 1, & 1-b < w_{ij} \leq 0.5 \\ \frac{(1-2w_{ij})}{2b-1} + 1, & 0.5 < w_{ij} < b \\ 0, & \text{elsewhere} \end{cases}$$

$$5.2 v_L(w_{ij}) = \begin{cases} \frac{(w_{ij}-1)}{(1-b)} + 1, & b < w_{ij} \leq 1 \\ 0, & \text{elsewhere} \end{cases}$$

$$5.3 v_S(w_{ij}) = \begin{cases} \frac{w_{ij}}{(b-1)} + 1, & 0 \leq w_{ij} \leq 1-b \\ 0, & \text{elsewhere} \end{cases}$$

6. Compute the Certainty Degree of the antecedents by applying the conjunction operation AND and disjunction operation OR by means of a t-norm $*$ and its associated S norm $*'$.

7. Weights are computed by defuzzification by Centre of Gravity Method

8. The weighted averaging filter operation on the pixel F_{22} is \tilde{F}_{22} given by

$$\left(\tilde{F}_{22} = \frac{\sum_{\substack{1 \leq i, j \leq 3 \\ 1 \leq n \leq m+1}} w_{ij}^n F_{ij}}{\sum_{\substack{1 \leq i, j \leq 3 \\ 1 \leq n \leq m+1}} w_{ij}^n} \right)$$

B. ADJUSTMENT OF PARAMETERS

The parameters involved in the proposed method are (m, s, k₁, k₂, a, b) where m shows the number of weighted pixels in the filtering window. Value of s gives the number of pixels used to determine the noisiness degree of a specific pixel. These parameters are selected based on the window size considering that only the least number of pixels should be involved so as to be able to reduce the Gaussian noise and less than a maximum number of pixels so as to avoid intensive image blurring.

In the work by Joan-Gerard Camarena [19], the PSNR performance has been analyzed on Lenna and Flower images degraded by the mixed noise model (Gaussian and salt and pepper noise). The 3 × 3 case has been studied, and by experiments, the parameters m and s are set to 7 and 2 respectively to optimize the overall PSNR.

The parameters k₁ and k₂ in (3) decide the degree of noisiness of a pixel from RODs (F_{ij}). If the value of RODs (F_{ij}) is less than k₁, then that pixel's noise degree is 0, if RODs (F_{ij}) is higher than k₂, then that pixel possesses a noise degree of 1. For those values that are intermediate, the certainty is given by the linear ascending relation. The values of k₁ and k₂ need to be set appropriately so as to obtain suitable certainty degrees and also they should be set as per the noise level of the image. Experimental results published by Joan-Gerard Camarena et al. proved that optimal PSNR values are obtained for k₁ that lies in the range [0.45RODmax, 0.55RODmax] and k₂ that lies in the range [0.55RODmax, 0.65RODmax] where

RODmax = max{RODs (F_{ij}) : F_{ij} ∈ F}. The values of k₁ and k₂ are fixed as k₁ = 0.5 x RODmax and k₂ = 0.6 x RODmax for optimal result [19]. These values have been adopted in this work.

The parameter a in (6) and (7) determine how the similarity degree is calculated. For lesser noise levels, a small value of a is appropriate, but its value needs to increase as the noise level rises. The appropriate value for a is related to the noise density in the image, since it intensely affects the similarities. A linear regression study was performed that relates a with σ as a = 0.998 σ + 1.960, thus automatically setting an adaptation to the noise level. Finally, the parameter b, which determines the weights of each pixel by defuzzification, has been set to 0.9, adopting the values from the experimental results published by Joan-Gerard Camarena et al. [19].

V. SIMULATION EXPERIMENT AND RESULTS

To evaluate the performance of the proposed filtering technique, images having distinct features from the Berkeley Segmentation Dataset [24] have been used. The classical model for Gaussian noise [3], [25] and impulse noises were considered. The performance of the filters has been evaluated using the peak signal-to-noise ratio (PSNR) which finds the noise suppression capacity. PSNR is a tool for measuring the distortion between the original and the recovered signals, which is evaluated on the decibel scale. It is a means to assess the restoration results, which measures how much close the restored image is to the original image. The PSNR values of the proposed method are compared with that of mean filter and SFRF technique. Table 1 displays the PSNR values of the mean filter, SFRF technique and the proposed method, for the flower image that is contaminated with noises of varying salt and pepper noise energy + Gaussian noise with σ=30. From Table.1, it is clear that the proposed filter outperforms Mean filter and Simple Fuzzy Rule Filter (SFRF).

Table 1: Performance in terms of PSNR values for σ=30

Noise	PSNR		
	Mean Filter	SFRF	Proposed Filter
Impulse Noise Energy (Percentage)			
10	40.5408	43.6108	46.3113
20	37.6475	40.1237	42.7956
30	35.2235	37.0200	39.8160
40	33.2502	34.3019	37.2633
50	31.1566	32.0366	35.0230
60	29.3633	30.9960	32.9475
70	27.7867	29.0532	31.0381
80	26.2215	27.5800	29.2514
90	24.7647	25.8197	27.8215

Fig. 5 shows the graphical analysis of performance of the mean filter, SFRF filter and proposed filter corresponding to Table 1. The graph clearly reveals that the PSNR value of the proposed filter is higher compared to mean filter and SFRF filter, which proves that the proposed filter exhibits better noise suppression capability.

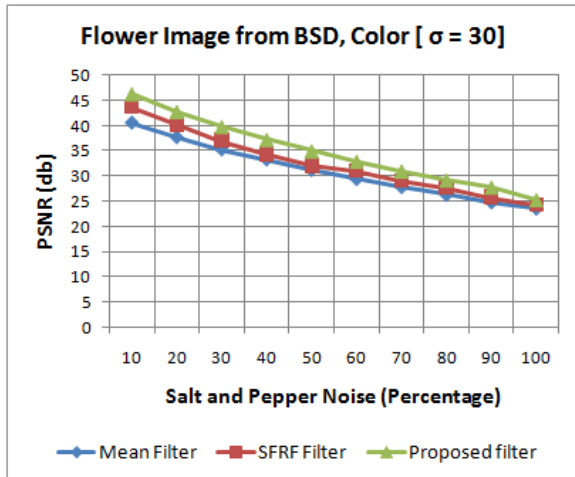


Figure 5: Comparison of PSNR values for the mean filter, SFRF filter and proposed color image filter for the flower image from Berkeley Segmentation Dataset corrupted by various densities of impulse noise, with Gaussian noise variance $\sigma=30$.

Fig. 6 (a) shows the original images from the Berkeley Segmentation Dataset. Fig 6 (b) shows images contaminated by mixed impulse noise energy of 10 percentage and Gaussian noise $\sigma=30$. 6 (c) shows the restored image after applying the proposed filter.

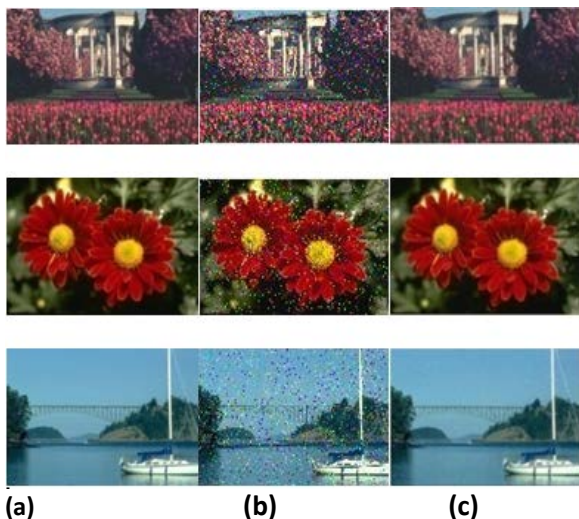


Figure 6: Outputs for visual comparison (a) Original images from Berkeley Segmentation dataset (b) Images corrupted with 10 % impulse

noise + Gaussian noise with $\sigma = 30$ (c) Restored image using proposed filter

VI. CONCLUSION

A novel and efficient noise filtering technique have been implemented to reduce mixed Gaussian and impulse noise, from color images. A modified certainty has been proposed to improve the filtering performance. Extensive computer simulations have proved that these methods reduce mixed noise significantly, while preserving image details and providing competitive results compared to state-of-the-art filter.

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