REDUCTION OF IMPULSE NOISE IN MONOCHROME IMAGES USING SOFT COMPUTING TECHNIQUES

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Abstract : A novel two-step fuzzy filter method that adopts a fuzzy logic approach for the improvement of images corrupted with impulse noise is presented in this paper. The method used for filtering is Fuzzy novel impulsive noise reduction method (FNINR) consists of a fuzzy noise detection mechanism and a fuzzy filtering method to remove both salt and pepper noise and random valued impulse noise from noise images. Based on the assumption of peak-signal-to-noise-ratio (PSNR) and subjective evaluations we have found experimentally, that the proposed method provides a significant improvement on other state of applications.

***IndexTerms* - Fuzzy filter, Salt & Pepper noise, Random valued impulse noise, Image restoration, Stable noise.**

I. INTRODUCTION

Fuzzy techniques have already been applied in several domains of image processing e.g. filtering, interpolation [29] and morphology [18,19]. They also have numerous practical applications (e.g., in industrial and medical image processing [20,3]). A major issue in the image processing techniques is that they cannot done properly in a noisy environment, so that a pre-processing module became necessary. In this paper, we will focus on fuzzy techniques for digital image filtering. More specifically we will concentrate on a fuzzy logic approach for the enhancement of images corrupted with impulse noise. Images are often corrupted with impulse noise due to a noisy sensor or channel transmission errors. The main goal of impulse noise reduction methods is to suppress the noise while preserving the fine texture and edge elements. It is found in the non-linear techniques that to provide more satisfactory results when comparing to other linear methods. A number of nonlinear approaches have been already developed for impulse noise removal, for example the well-known fuzzy inference rule by else-action filters (FIRE). These filters try to calculate positive and negative correction terms in order to express the degree of noise for a certain pixel. We distinguish three FIRE filters: the normal FIRE from [23], the dual step FIRE from [24] (DS-FIRE) and the piecewise linear FIRE from [21] (PWLFIRE). The adaptive weighted fuzzy mean filter [17,16] (AWFM), the histogram adaptive fuzzy filter [30,31] (HAF), the intelligent image agent based on soft-computing techniques [8] (IIA) and the adaptive fuzzy switching filter (AFSF), which uses the maximum–minimum exclusive median filter [32], are other examples of the state-of-the-art methods. These fuzzy filters are mainly developed for images corrupted with fat-tailed noise like impulse noise. They are also able to outperform rank-order filter schemes (such as the median filter). Examples of real impulse noise include atmospheric noise, cellular communication, underwater acoustics and moving traffic. Recently, it has been shown that α-stable distributions can approximate impulse noise more accurately than other models [13, 2]. The goal of this paper is to develop an impulse noise reduction method, which performs well for this, more realistic, kind of randomly valued impulse noise model. The paper structure is organized as follows: in Section 2 we explain the detection method. The filtering method of the new filter (FINR) is discussed in Section 3. In Section 4 we present several experimental results. These results are discussed in detail, and are compared to those obtained by other filters. Some final conclusions are drawn in Section 5.

(A) IMPULSE NOISE MODELS

In many impulse noise models for images, corrupted pixels are often replaced with values equal to or near the maximum or minimum intensity values of the allowable dynamic range. This typically corresponds to fixed values near 0 or 255 (for a 8-bit image). In this paper, we consider a more general noise model in which a noisy pixel is taken as an arbitrary value in the range according to some function of probability distribution. Let X (i, j) and Y (i, j) denote the intensity value, at position η (i, j), of the original and the noisy image, respectively. Then, for an impulse noise model with error probability pr, we have

$$X(i,j) = \begin{cases} Y(i,j) \text{ with probability } 1 - pr, \\ \eta(i,j) \text{ with probability } pr, \end{cases} \quad (1)$$

where η(i,j) is an identically distributed, independent random process with an arbitrary underlying probability density function. Recently, it has been shown that an α-stable distribution can approximate impulse noise more accurately than other models. Therefore this type of randomly distributed impulse noise has been used. The parameter α controls the degree of impulsiveness and the impulsiveness increases as α decreases. The Gaussian (α = 2) and the Cauchy (α= 1) distributions are the

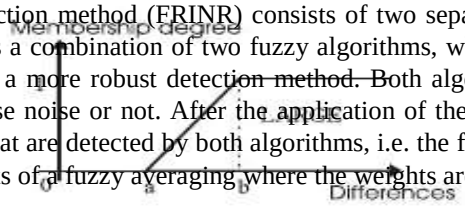
only symmetric α-stable distributions that have continuous probability density functions. A symmetric α-stable ($S\alpha S$) random variable is only described by its characteristic function:

$$Ø(t) = \exp\,(j\theta t - \gamma|t|^{\alpha}), \tag{2}$$

where $j \in C$ is the imaginary unit, $\theta \in R$ is the location parameter (centrality), $\gamma \in R$ is the dispersion of the distribution and $\alpha \in [0, 2]$, which controls the heaviness of the tails, is the characteristic exponent. For more background information about the α-stable noise model we refer to [13,2].

(B) THE FINR METHOD

The Fuzzy Impulsive Noise Reduction method (FRINR) consists of two separated phases: the detection phase and the filtering phase. The phase of detection is a combination of two fuzzy algorithms, which are complementary to each other and which are combined together to receive a more robust detection method. Both algorithms use fuzzy rules [27] to determine whether a pixel is corrupted with impulse noise or not. After the application of the two fuzzy algorithms, our fuzzy filtering technique focuses only on those pixels that are detected by both algorithms, i.e. the filtering is concentrated on the real impulse noise pixels. The filtering method consists of a fuzzy averaging where the weights are constructed using a predefined fuzzy set.



II. NOISE DETECTION METHOD

The proposed detection method is composed of two subunits that are both used to define corrupted impulse noise pixels. The first subunit investigates the neighborhood around a pixel to conclude if the pixel can be considered as impulsive noise or not. The second subunit uses fuzzy gradient values [28] to determine the degree in which a pixel can be considered as impulse noise and the degree in which a pixel can be considered as noise free.

Detection mechanism unit

We consider a two dimensional input image denoted as A. The goal of the first detection unit is to determine if a certain image pixel A (i,j), at position (i, j), is corrupted with impulse noise or not. Therefore we observe the elements in a (2M + 1) × (2M + 1) (with M≥1) window centered around A (i, j). Next, we calculate the mean differences in this window denoted as g (i, j):

$$g(i,j) = \frac{\sum_{m=-M}^{M}\sum_{l=-M}^{M}|A(i+m,j+l)-A(i,j)|}{(2M+1)^2-1} \tag{3}$$

Corrupted impulse noise pixels generally cause large g(i, j) values, because impulse noise pixels normally occur as outliners in a small neighborhood (during this paper we consider M = 1) around the pixel. On the other hand we also found that the g(i,j)-value could be relatively large in case of an edge pixel. Therefore we have considered the following two values denoted as a(i, j) and b(i, j):

$$a(i,j) = \frac{\sum_{m=-M}^{M}\sum_{l=-M}^{M} g(i+m,j+l)}{(2M+1)^2} \tag{4}$$

$$b(i,j)=g(i,j) \tag{5}$$

If both values (a (i, j) and b (i, j)) are large, then the pixel can be considered as an edge pixel instead of a noisy one. So when the two values (a (i, j) and b (i, j)) are very similar we conclude that the pixel is noise free. Otherwise, if the difference between a (i, j) and b (i, j) is large then we consider the pixel as noisy. This can be implemented by the following fuzzy rule:

Rule 1. Defining when a central pixel A (i, j) is corrupted with impulse noise: IF |a (i, j) − b (i, j)| is large, THEN the central pixel A (i, j) is an impulsive noise pixel.

In this rule, large can be represented as a fuzzy set [11]. A fuzzy set in turn can be represented by a membership function. An example of a membership function LARGE (for the corresponding fuzzy set large), which is entitled as β_{large} is pictured in Fig. 1. From such functions we can derive membership degrees. If the difference |a(i, j) −b(i, j)| for example has a membership degree one (or zero) in the fuzzy set large, it means that this difference is considered as large (or not large) for sure. Membership degrees between zero and one indicate that we do not know for sure if such difference is large or not, so that the difference is large to a certain degree. For more background information about fuzzy set theory we refer to Kerre [11]. In Fig. 1 we see that we have to determine two important parameters c and d The parameter *a* is equal to the lowest g (i + m, j + l) value in the (2M + 1) × (2M + 1) window around the central pixel, i.e.

$$c(i,j)_{=m,l\in(-M,\ldots+M)}\min g(i+m,j+l) \tag{6}$$

So, c(i, j) corresponds to the g(i +m, j +l) coming from the most homogeneous region around A(i, j), which should correspond to the region with the smallest amount of impulse noise pixels. Experimental results have shown that the best choice for parameter d(i, j) is d(i, j) = c(i, j) + 0.2 c(i, j), i.e. the larger the parameter a, the larger the uncertainty interval [c, d] should be. So, the outputs

of the first detection method are the membership degrees in the fuzzy set impulse noise for each pixel separately. The membership function that represents this fuzzy set is denoted as _impulse. The corresponding membership degrees (∈[0, 1]) are calculated using Rule 1. The activation degree of this rule is used to determine the membership degree $\beta_{impulse}$, i.e. $\beta_{impulse}$ $(A(i, j)) = \beta_{large}(|a(i, j) - b(i, j|))$.As for the first detection unit, also for the second one, to calculate the degree in which a certain pixel A(I, j)can be considered as impulse noise. Both units of detection are complementary to each other, i.e. by combining them we receive a more robust detection method that improves the global performance.

Fig. 1. The membership function LARGE denoted as large.

We again use a (2M + 1) × (2M + 1) (we have used M = 1) neighborhoods around A(I, j) as illustrated in Fig. 2. Each of the eight neighbours of A(I, j) corresponds to one direction {North West (NW), North (N), North East (NE), East (E), South East (SE), South (S), South West (SW), West (W)}. Next, we define the gradient value γ A(I, j) of pixel position (I, j) in direction D, which corresponds to a certain position (shown in Fig. 2) as,

$$\gamma(m,l)A(I, j) = A(I + m, j + l) - A(I, j) \quad m, l \in \{-M,\dots M\}, \tag{7}$$

where the pair (m,l) corresponds to one of the eight directions and (I,j) is called the centre of the gradient. The eight gradient values (associated to the eight directions or neighbours) are called the basic gradient values. There are two cases where large gradient values occur: (1) if one of the two pixels is corrupted with impulse noise or (2) when an edge is presented. To detect the case using rule 1and therefore we use not only one basic gradient value for each direction but also two related gradient values (defined in the same direction). These two related gradient values in the same direction as the basic gradient are determined by the centres making a right-angle with the direction of the corresponding basic gradient. This is illustrated in Fig. 3 for the NW-direction (i.e. for (m, l) = (+1,+1)). The basic gradient and the two related gradient values at position (I, j) are defined as ,γ (−1,−1)A(I, j), γ (−1,−1)A(I −1, j +1) and γ (−1,−1)A(I + 1, j – 1), respectively.

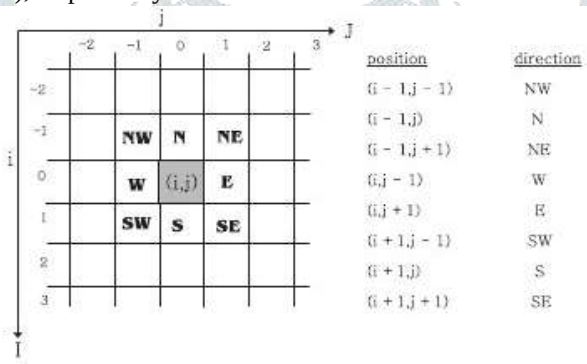


Fig. 2. A neighborhood of a central pixel A(i, j).

In Table 1 we give an overview of the involved gradient values: each direction *D* (column 1) corresponds to a position (Fig. 2) with respect to a central position. Column 2 states the basic gradient for each direction, column 3 lists the two related gradients. For each direction we will finally calculate a membership degree in the fuzzy set impulsive noise(denoted as $\mu^{D}_{impulse}$ for direction D) and the membership degree in the fuzzy set impulsive noise free (denoted as μ^{D}_{free} for direction D). This is realized by the following Fuzzy Rules 2 and 3.

Rule 2. Defining when a central pixel A (I, j) is corrupted with impulse noise for a certain direction D.,

IF (|χ A (I, j)| is **not** large) AND (|χ A (I, j)| is large) AND (|χ A(I, j)| is large).

Rule 3. Defining when a central pixel A (I, j) is not corrupted with impulse noise for a certain direction D:

IF (|ά A(I, j)| is large) AND (|ά A(I, j)| is large) AND
(|ά A(i, j)| is large) OR (|ά A(I, j)| is not large) AND
(|ά A(I, j)| is not large) AND (|ά A(I, j)| is not large)THEN the central pixel A(I, j) is impulse noise free in direction D.

We have denoted the basic gradient as β A (I, j), while the two related gradient values were entitled as χA(I, j) and ά A(I, j), respectively. Fuzzy Rule 2 determines when a certain pixel can be observed as impulse noise or not. This rule contains conjunctions and disjunctions. In fuzzy logic triangular norms and co-norms are used to represent conjunction (roughly the equivalent of the AND operator) and disjunction (roughly the equivalent of the OR operator)[5]. Two well-known triangular norms (together with their dual co-norms) are the product (probabilistic sum) and the minimum (maximum). In fuzzy logic involutive negators are

commonly used to represent negations. We use the standard negator Ns(x) = 1 – x, with x ∈ [0, 1]. We illustrate the concept of triangular norm and standard negator with a short example: the fuzzification of the following statement, i.e. we assign a value in the unit interval to indicate the truthness of this statement (1 indicates that this statement is true for sure and 0 indicates that this statement is false for sure), "*(|β A(I, j)| is not large) AND (|χA(I, j)| is large) AND (|ά A(I, j)| is large)*'' is calculated by*(1−μ*large*(|β A(I, j)|)) · μ*large*(|χ A(I, j)|) · μ*large*(|ά A(I, j)|)*, where we used the "product'' triangular norm and where large has the same graph as in Fig. 1 using the following parameters *a* and *b*:

$$a(i,j) = \frac{\sum_{m=-M}^{M}\sum_{l=-M}^{M} g(i+m,j+l)}{(2M+1)^2} \tag{8}$$

$$b(i, j) = a(i, j) + a(i, j) * 0.2 \tag{9}$$

So, a(i, j) corresponds to the average of the g(i + k, j + l) values. By using these parameters we have managed the incorporation of regions containing edges, because these non-homogeneous regions will cause higher parameters so that our detection method is adapted to such situations. Gradient values in non-homogeneous regions are labeled as large if they are large in comparison to their neighbours. In homogeneous regions we will get smaller values of a(i, j) and b(i, j), which will cause a much stronger detection method. The outputs of the second detection unit are the eight membership degrees in the fuzzy set impulse noise for the eight directions around a certain position (i, j), i.e. the degrees $\mu^{D}_{impulse}$ A (i, j) and the eight membership degrees in the fuzzy set impulse noise free for the eight directions around a certain position (i, j) i.e. the degrees μ^{D}_{free} A(i, j).The degrees $\mu^{D}_{impulse}$ A(i, j) and μ^{D}_{free} A(i, j) are calculated using Fuzzy Rule 2 and 3, respectively.

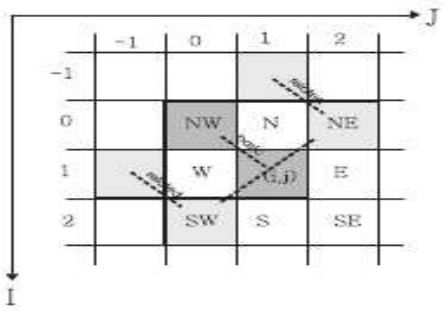


Fig. 3. Involved centres for the calculation of the related gradient values in the NW-direction.

III FUZZY BASED FILTERING METHOD

We combine both detection units to determine the pixels where the filtering method will be applied, i.e. we will apply the filtering method on pixels that are determined as noisy in both units. Pixels having a non-zero membership degree in the fuzzy set impulsive noise for the first detection unit are considered as noisy, i.e. $\mu^{D}_{impulse}$ (A(i, j)) > 0. In the second detection unit we consider two fuzzy sets namely impulsive noise and impulse noise free in order to decide if a pixel is considered as noisy or not. Here we have decided that the impulse noise is considered at A (i, j). So, the filtering method will be applied to pixels where both restrictions are satisfied, i.e.

$$\mu_{impulse}(A\ (i, j\ )) > 0, \tag{10}$$

$$\sum_{D\in\{N,.....S\}} \mu^{D}_{impulse}\, A(i,j) \geq \sum_{D\in\{N,.....S\}} \mu^{D}_{free}\, A(i,j) \tag{11}$$

The output of the filtering method for the input pixel A(i, j) is denoted as F(i, j) and is calculated as follows:

$$F(i,j) = \left(1-\lambda(i,j)\right)\frac{\sum_{m=-L}^{L}\sum_{l=-L}^{L} A(i+m,j+l)p(i+m,j+l)}{\sum_{m=-L}^{L}\sum_{l=-L}^{L} p(i+l,j+m)} + \lambda(i,j)A(i,j) \tag{12}$$

The filtering method uses a (2L+1)×(2L+1) (not necessary equal to K) neighborhood around A(i, j) as shown in expression 12. Each A(i + m,l + l) is multiplied by a corresponding weight p(i +m, j +l) indicating in which degree the pixel should be used (explained later) to filter the central pixel. The parameter λ(i, j) is finally used to control the amount of correction.
To determine the weights, we have used the pixels from the (2M + 1) × (2M + 1) neighborhood around A(i, j)(with the same M as in the detection method). Those pixels are then sorted so that the window is denoted as [y1, y2, ...,y(2M+1)2] with y1 and y(2M+1)2 the lowest and highest intensity value from the corresponding window, respectively. We do not replace the corrupted pixels by their

median, but nevertheless we try to use the other pixels in the neighborhood as well. When the (2M + 1) × (2M + 1) neighborhood is very homogeneous we know that median based algorithms are working very well, but when we have non-homogeneous neighborhoods it is better to incorporate the knowledge of the other pixels as well to improve the filtering performance. Therefore we have constructed a fuzzy set called similar to calculate the corresponding weights w(i+m, j+l). This fuzzy set is represented by the membership function SIMILAR, pictured in Fig. and denoted as μ_{sim}. The membership value indicates in which degree a certain intensity value can be observed as similar to the observed neighborhood. Pixels having a degree of one (zero) are (not) similar for sure to the corresponding neighborhood. So the weight p(i +k, j +l) is defined as p(i +k, j +l) = μ_{sim} (A(i + k, j + l)). The membership function is determined by means of four parameters. To define these parameters (p1, p2, q1 and q2) we first have calculated the mean differences δ, i.e.

$$\delta(i,j) = \frac{\sum_{m=2}^{(2M+1)^2}(x_m - x_{m-1})}{(2M+1)^2-1} \tag{13}$$

Using this δ(i, j) we have determined the parameters as follows:

$$x(i,j) = \underset{m,l\in(-M,\ldots,+M\}}{\overset{median}{}} A(i+m, j+l) \tag{14}$$

$$p1(i, j) = x(i, j) - \delta(i, j), \; p2(i, j) = x(i, j) - 1.1\delta(i, j),$$

$$q1(i, j) = x(i, j) + \delta(i, j), \; q2(i, j) = x(i, j) + 1.1\delta(i, j). \tag{15}$$

Homogeneous regions will have very similar pixels, which will cause very low (i,j) values, because the differences between the pixel intensity values will be low. In these situations we will receive parameters (p1(i, j), p2(i, j), q1(i, j) and q2(i, j)) that are very close to the median (the centre of the fuzzy set) and therefore the filtering performance will be similar to median based filters.

On the other hand we will get an improvement in cases of non-homogeneous windows, because we still incorporate the information of all the neighboring pixels around A(i, j) as well. Finally, we will reduce the correction process for the central pixels A(i, j) having a very high weight p(i,j) because if the corresponding weight is very high, it means that these pixels seem to be similar to their neighborhood unless the detection. Therefore we define the parameter λ(i, j) to be equal to the weight of the centre, i.e. λ(i, j) = p(i, j).

IV EXPERIMENTAL RESULTS

In this section, we compare the performance of proposed method (FINR) with some state-of-the-art methods for reducing impulse noise from digital monochrome images is shown in Table I. The experiments were carried out on the well-known test images: "house"and "Real'' that are, respectively, 512×512 pixel The objective quantitative measured used for comparison are the peak signal-to-noise ratio (PSNR) between the original and restored images, defined by

$$PSNR = log_{10}\frac{size^2}{\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}[f(i,j)-\hat{f}(i,j)]^2} \tag{16}$$

where f is the original image, $\hat{f}$ the restored image of size MN and size the maximum possible intensity value (with 8-bit the maximum will be 255).

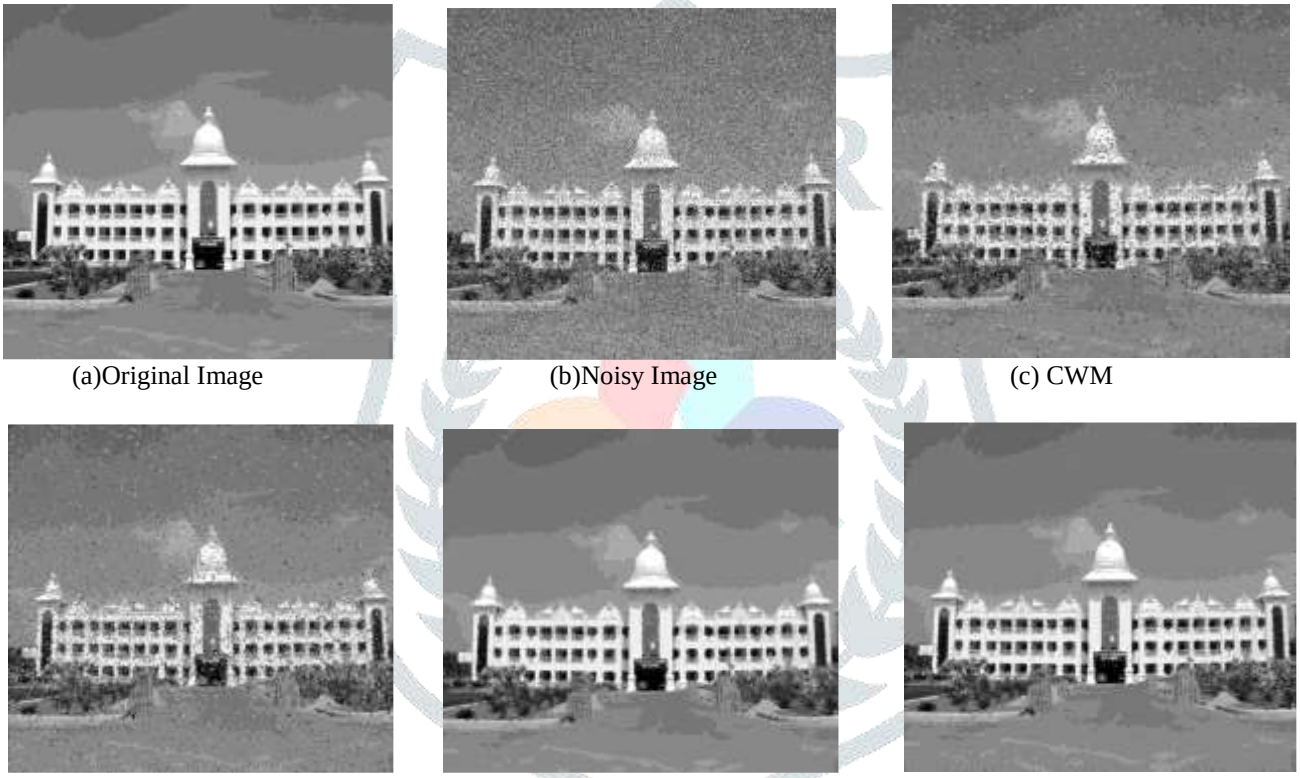
(a) Original Image

(b) Noisy Image

(c)CWM

(d) FIRE (e) AWFM (f) Proposed

Fig. 4. Results of Different Methods in restoring 20 percent corrupted image "House".



(a)Original Image (b)Noisy Image (c) CWM

(d) FIRE (e) AWFM (f) Proposed

Fig. 5. Results of Different Methods in restoring 20 percent corrupted image "Real".

TABLE I
PSNR (dB) results for House image on different level of noise densities

Noise Density (%)	CWM	FIRE	AWFM	Proposed
5	34.04	36.79	37.94	38.54
10	32.93	34.89	35.80	36.06
15	31.41	32.37	33.05	34.72
20	28.59	30.04	32.87	33.38
50	23.09	21.89	29.75	30.42
70	14.60	17.03	20.11	24.60
90	11.51	12.55	14.17	17.82

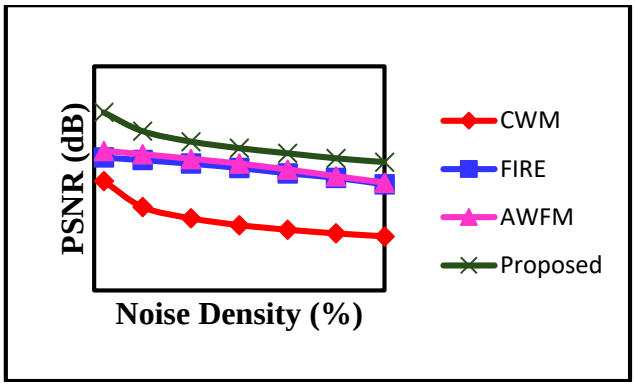


Fig. 6. Comparison graph of various denoising method

V CONCLUSION

A novel fuzzy impulsive noise reduction method (FINR), which consists of two fuzzy detection methods and a fuzzy filtering algorithm, has been presented in this paper. This filter is especially developed for reducing all kind of impulsive noise (i.e., salt & pepper noise and random valued impulsive noise). Its main advantage is that it removes impulsive noise very well while preserving the fine image details. Additionally, the proposed filter yields better performance when compared to other method. Experimental results have shown the feasibility of the novel filter. A numerical results, such as the PSNR (Peak signal to noise ratio, and observations (Fig. 4 and 5) have shown conculsive results for monochrome images.

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