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A Fuzzy Random Impulse Noise Detection and Reduction Method Based on Noise Density Estimation

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Abstract— In this paper a new method is proposed for restoring images that are corrupted with random valued impulse noise. The proposed method employs the fuzzy logic approach and consists of three main steps: Noise density estimation, fuzzy noise detection and fuzzy noise reduction. In the fuzzy noise detection step, a fuzzy set Noise-Free is constructed based on the rank-ordered mean of the absolute differences and the estimated noise density to determine whether a certain pixel can be considered as a noisy or noise-free. While in the fuzzy noise reduction step, another fuzzy set Similar is constructed to determine the similarity degree for each pixel in the observed window. These two fuzzy sets are used together to determine the final fuzzy weight to each pixel for restoring the corrupted image pixels. Experimental results that based on peak signal to noise ratio, edge measure and visual observation show that the proposed method provides good results for noise suppression and detail preservation as well as outperforms many well-known filtering techniques.

الخلاصة— في هذا البحث اُقترحت طريقة جديدة لاسترجاع الصور الملوثة بالضوضاء النبضية العشوائية القيمة (Random valued impulse noise). تستخدم الطريقة المقترحة تقنية المنطق المضبب وتتكون من ثلاثة خطوات رئيسية: تخمين كثافة الضوضاء, كشف الضوضاء المضبب, ازالة الضوضاء. في خطوة كشف الضوضاء المضبب تُكون مجموعة مضببة (Noise-free) بلاعتماد على معدل مطلق الفرق المرتب (Rank-ordered mean of the absolute difference) وكثافة الضوضاء المُقدرة لتحديد فيما اذا يمكن اعتبار الـ (pixel) ملوث او نظيف. بينما في خطوة ازالة الضوضاء تُكون مجموعة مضببة اخرى (Similar) لتحديد درجة التشابه لكل (pixels) ضمن المنطقة المعالجة (observed window) . تُستخدم هاتان المجموعتان المضببة لتحديد الوزن النهائي المضبب لكل (pixel) لاسترجاع الـ (pixels) الملوثة. بينت النتائج العملية التي اعتمدت على قمة الاشارة الى نسبة الضوضاء (PSNR) وعلى مقياس الحافة وعلى الملاحظة البصرية ان الطريقة المُقترحة تعطي نتائج جيدة فـي ازالة الضوضاء والمحافظة على تفاصيل الصورة بالاضافة الى تفوقها على العديد من تقنيات التصفية المعروفة.

Index Terms— Fuzzy logic, noise detection, noise reduction, random noise, impulse noise, edge measure.

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1 INTRODUCTION

In many of digital image processing application, observed image is often corrupted by noise which may arise during image acquisition or image transmission. Noise reduces image quality and lead to unwanted results of subsequent steps of the image processing (e.g., segmentation, parameter estimation, and enhancement). Hence, removal of noise from images is one of the most significant tasks in image processing. Impulse noise is one of the most widespread and important noise in digital images and consists of relatively short duration 'on/off' noise pulses. It affects images at the time of acquisition due to noisy sensors (switching, sensor temperature) or at the time of transmission due to channel errors (interference, atmospheric disturbances) or faulty memory locations in hardware or by synchronization errors (analog-to-digital conversion) during image processing

[1,2]. The model of impulse noise considered in this paper is the Random Valued Impulse Noise (RVIN). Among various impulse noise reduction methods, the median filter [3] is widely used due to its noise suppression capability with high computational efficiency. The median filter often destroys image details and blurs image too because every pixel in the image is replaced by the median value of its neighborhood. The center-weighted median filter [4] was proposed to improve the median filter by giving more weight only to the center pixel in the observed window. Although this filter can preserve more details than the median filter, it is still applied uniformly across the image without determining the noisy or noise free pixels. In order to improve the median filter, many filters with an impulse detector are proposed, such as adaptive center weighted median (ACWM) filter [5], directional weighted median (DWM) filter [6], second order difference based detection and directional weighted median (SOD-DWM) filter [7]. Recently, many noise reduction methods based on fuzzy techniques are developed such as cluster-based adaptive fuzzy switching median (CAFSM) filter [8] and directional weighted median base fuzzy filter (DWMFF) [9].

In this paper, we propose a new Fuzzy Random Impulse Noise Detection and Reduction (FRINDR) method for RVIN removing from images based on fuzzy techniques and the estimated noise density. The noise density is firstly estimated for two purposes: the first is to determine the window size used in the fuzzy noise detection step and the second purpose is to determine the shape of the membership function which is also used in the fuzzy noise detection step.

2 Noise density estimation

In this section, the model of random valued impulse noise and the proposed method for noise density estimation are described.

2.1 Noise model

Impulse noise is always independent and uncorrelated to the image pixels, a number of image pixels will be noisy and the rest of pixels will be noise free. In case of random valued impulse noise (also known as uniform impulse noise), the noisy pixel take any value in the gray level range, i.e., $[L_{min}, L_{max}]$ for 8-bit image representation. Hence, the noisy pixel will be taking any value in the gray level range from 0 to 255. In this case also noise is randomly distributed over the entire image and probability of occurrence of any gray level value as noise will be same [8]. The RVIN model can be described as follows:

$$I(x,y) = \begin{cases} n(x,y), & \text{with probability } P \\ O(x,y), & \text{with probability } 1-P \end{cases} \qquad \dots (1)$$

Where, $I(x,y)$ is the noisy image pixel, $O(x,y)$ is the uncorrupted image pixel and $n(x,y)$ is the noisy impulsive pixel at position (x, y).

2.2 Noise density estimation steps

To estimate the noise density, the observed image is divided into 16 non-overlapping blocks (B_i) with $i \in \{1,2,\ldots,16\}$ and then the noise density for each image block is estimated as follows:

1- Calculate the standard deviation (std_i) for the whole current block B_i using the following equation:

$$std_i = \sqrt{\frac{1}{M_{B_i} \times N_{B_i}} \sum_{(x,y)\in B_i} (I(x,y) - m_i)^2} \qquad \dots (2)$$

where, m_i : is the mean value of current block B_i
$I(x,y)$: is the pixel data inside B_i and $(M_{Bi} \times N_{Bi})$ is the size of the current block B_i.

2- Scan the entire image block B_i using a 3x3 sliding window from pixel to pixel and calculate the following in each scan:

i) let D_{xy}^{N4} denotes the set of absolute differences between the central pixel and its four nearest neighbors in the considered window,

$$D_{xy}^{N4} = |I(x+s, y+t) - I(x,y)| \;\; with\; s,t \in S_{N4} \qquad \dots (3)$$

Where, S_{N4} represents the set of coordinates for the four neighbors of $I(x,y)$ and given by:

$$S_{N4} = \{(-1,0),(1,0),(0,-1),(0,1)\} \qquad \dots (4)$$

Then the elements in D_{xy}^{N4} can be arranged in ascending order such that,

$$d_{xy}^1 \le d_{xy}^2 \le d_{xy}^3 \le d_{xy}^4$$

ii) Define v_{xy} which represents the median value of the D_{xy}^{N4} elements by the following equation:

$$v_{xy} = \frac{d_{xy}^2 + d_{xy}^3}{2} \qquad \dots (5)$$

iii) Employ the standard deviation (std_i) of the observed image block and the value of v_{xy} to identify the current pixel $I(x,y)$ as follows:

$$M_{RV}(x,y) = \begin{cases} 1, & v_{xy} > std_i \\ 0, & v_{xy} \le std_i \end{cases} \qquad \dots (6)$$

Where, $M_{RV}(x,y)$ represents the decision rule for estimating RVIN density.

3- The noise density ND_{RV} for the first block is given as:

$$ND_{RV}^{Bi} = CF \times \frac{\sum_{(x,y)\in B_i} M_{RV}(x,y)}{M_{Bi} \times N_{Bi}} \times 100\% \qquad \dots (7)$$

Where $M_{Bi} \times N_{Bi}$ represents the size of the current block B_i and CF represents the control factor which is estimated by experiments. Experimental results have shown that the best choice for parameter CF is $CF = 1.35$.

4- Define the minimum value of (ND_{RV}^{Bi}) as:

$$ND_{min} = \min_{1\le i\le 16} \left(ND_{RV}^{Bi}\right) \quad , \text{with } i \in \{1,2,\dots,16\} \qquad \dots (8)$$

5- If ND_{min} is smaller than one, then the image is considered clean as for random value impulse noise. Otherwise, the image is considered corrupted with RVIN and the noise density of the entire image is equal to the mean value of the noise densities of all blocks and given as follows:

$$ND_{\mathrm{RV}} = \begin{cases} 0, & \text{if} \quad ND_{\min} < 1 \\ \mathrm{mean}_{1 \le i \le 16}\left(ND_{\mathrm{RV}}^{\mathrm{B}i}\right) & \text{otherwise} \end{cases} \quad \ldots (9)$$

Where, ND_{RV} is the RVIN density for the entire image.

Table 1 illustrates the difference between the estimated noise density and the real noise density using "Lena", "Cameraman", "Baboon", "Parrot", "Peppers", "Airplane", "Boats", "Bridge" images corrupted with wide range of RVIN ranging from 5% to 60%. It is clear from table 1 that the proposed method obtains successful results in noise density estimation where the estimation error is still below 6%.

Table (1): The estimated noise density for eight images corrupted with wide range of RVIN (10%-60%).

Real noise density	Lena	Cameraman	Baboon	Parrot	Peppers	Airplane	Boats	Bridge
5%	5.9%	6.6%	10.8%	6.0%	5.1%	6.5%	7.4%	6.9%
10%	10.6%	11.9%	15.6%	10.6%	9.8%	11.4%	13.1%	11.5%
20%	21.1%	22.0%	25.4%	20.9%	19.7%	22.2%	23.5%	21.7%
30%	30.7%	31.9%	35.9%	30.4%	30.0%	31.9%	33.5%	31.8%
40%	40.6%	41.6%	44.8%	40.4%	39.6%	41.9%	43.4%	41.3%
50%	49.0%	50.0%	52.8%	48.8%	48.2%	50.4%	51.7%	49.7%
60%	57.0%	57.0%	58.3%	56.8%	56.5%	57.3%	57.8%	56.8%

3 Noise Detection

As mentioned in section (2), in RVIN situation, a noisy pixel can take any value in the gray level range, i.e. [0-255] for 8-bit image representation and can be different slightly in intensity from the original one. Therefore, cleaning such a noise is far more difficult than cleaning SPN and required a robust detection scheme. The proposed method utilizes the Rank-Ordered Mean of the Absolute Differences (ROMAD) and the estimated noise density incorporated with the fuzzy logic. The rank-ordered mean difference is calculated between the central pixel and its surrounding pixels under the considered $(2K+1)\times(2K+1)$ sliding window for every pixel in the image. The value of K is set adaptively to the noise density since $\mathrm{K}=1$ when ($ND_{\mathrm{RV}} <$ 35%) otherwise, $K = 2$.

In order to calculate (ROMAD) for a certain pixel $I(x, y)$, the following three steps are required:

1- Calculate the absolute differences D_{xy} between the current pixel $I(x, y)$ and the other surrounding pixels within the observed window by :

$$D_{xy} = |I(x+s, y+t) - I(x, y)| \text{ with } s, t \in \{-K, \ldots, +K\}, (s,t) \neq (0,0) \quad \ldots (10)$$

Where, $I(x+s, y+t)$ represents the pixels values in the observed window.

2- Let d_{xy}^{i} be the ith smallest ranked value in D_{xy} when the elements of D_{xy} are arranged in ascending order, such that

$$d_{xy}^{1} \le d_{xy}^{2} \le \cdots \le d_{xy}^{u}$$

Where, u is the number of the central pixel neighbors within the observed window $(2K+1)\times(2K+1)$. So, $u = ((2K+1)^2 - 1)$

3- The (ROMAD) for the current pixel is defined as:

$$R_{xy} = \frac{\sum_{i=1}^{n} d_{xy}^{i}}{n} \quad \text{... (11)}$$

Where, $n = u - 2(2K-1)$ ... (12)

After calculating ROMAD for every pixel of the image, the value of ROMAD can be a good measure for distinguishing between the noisy and noise free pixels. So when the noise ratio is low and the value of ROMAD for a certain pixel $I(x,y)$ is small, this means that the pixel is a noise free and belongs to homogeneous neighborhood. Whereas, larger value of ROMAD means that the pixel is either a noisy or an edge pixel. Hence, the linguistic value small is represented as a fuzzy set namely *"Small ROMAD"* by the membership function μ_{small} as shown in Fig. 1 to determine the noise free pixels. However, the value of ROMAD will be always relatively large when the noise ratio is high. To overcome this problem, the membership function μ_{small} of the fuzzy set *"Small ROMAD"* can be constructed (i.e. determining its parameters) adaptively for each neighborhood according to two criterions. These criterions are:
First: the neighborhood homogeneity level (H_{xy}) around the tested pixel $I(x,y)$.
Second: the noise density of entire image.

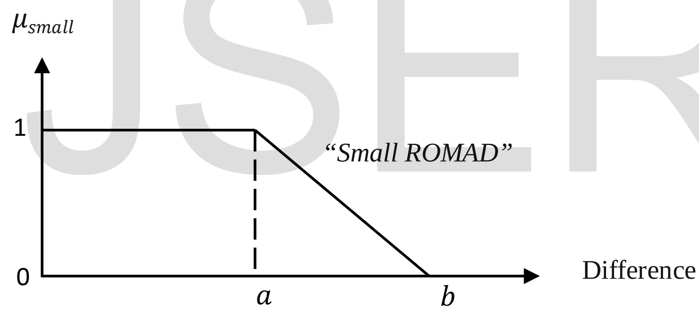

Fig. 1: Membership function μ_{small} of fuzzy set *"Small ROMAD"*

The membership function μ_{small} is described by the following equations:

$$\mu_{small}(R_{xy}) = \begin{cases} 1, & R_{xy} < a \\ \frac{b - R_{xy}}{b-a}, & a \le R_{xy} \le b \\ 0, & R_{xy} > b \end{cases} \quad \text{... (13)}$$

Where:

$a = H_{xy} \times NF_{\mathrm{RV}}$ ... (14)
$b = q \times NF_{\mathrm{RV}}$ ... (15)

Where, NF_{RV} represents the noise factor of the RVIN,
q is the nth smallest value in $R_{(x+s,y+t)}$.
Furthermore, the values of H_{xy} , NF_{RV} and q are obtained below:

Firstly, the value of H_{xy} can be calculated by employing the values of ROMAD in the observed window as follows:

1- Let r_i be the ith smallest ranked value in $R_{(x+s,y+t)}$ when the elements of $R_{(x+s,y+t)}$ are arranged in ascending order, such that:

$$r_1 \leq r_2 \leq \cdots \leq r_u$$

Where, $u = ((2K+1)^2 - 1)$

2- Calculate the value of H_{xy} as:

$$H_{xy} = \frac{\sum_{i=1}^{n} r_i}{n} \qquad \text{... (16)}$$

Secondly, the value of q is calculated by:

$$q = r_n \qquad \text{... (17)}$$

Thirdly, the value of NF_{RV} can be obtained by employing the equation of a straight line as shown in Fig. 2 and given by:

$$NF_{\text{RV}} = \frac{P_1 * (P_3 - ND_{\text{RV}})}{P_3 - P_2} \qquad \text{... (18)}$$

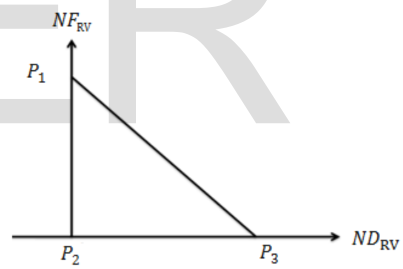

Fig. 2: The function of NF_{RV}

Where, the parameters (P_1, P_2 and P_3) are estimated by experiments. Experimental results have shown that the best choice for the parameters (P_1, P_2 and P_3) are equal to (2.9, 0, 61) respectively when the estimated noise density is below or equal to (35%) and (P_1, P_2 and P_3) are equal to (1.9, 20, 100) respectively when the estimated noise density is more than (35%)

Ultimately, for each tested pixel $I(x,y)$, a fuzzy set *"Noise-Free"* is derived by the following fuzzy rules:
Fuzzy Rule 1: Defined when a central pixel $\boldsymbol{I(x,y)}$ is a noise free pixel:
IF $\boldsymbol{R_{xy}}$ is small
THEN the central pixel $\boldsymbol{I(x,y)}$ is noise- free
This rule can be implemented using the equality operation of two fuzzy sets. Thus, the membership function of the fuzzy set *"Noise-Free"* is obtained by:

$$\mu_{noisefree}(I(x,y)) = \mu_{small}(R_{xy}) \qquad \text{... (19)}$$

Additionally, the flowchart of RVIN detection steps is shown in Fig. 3.

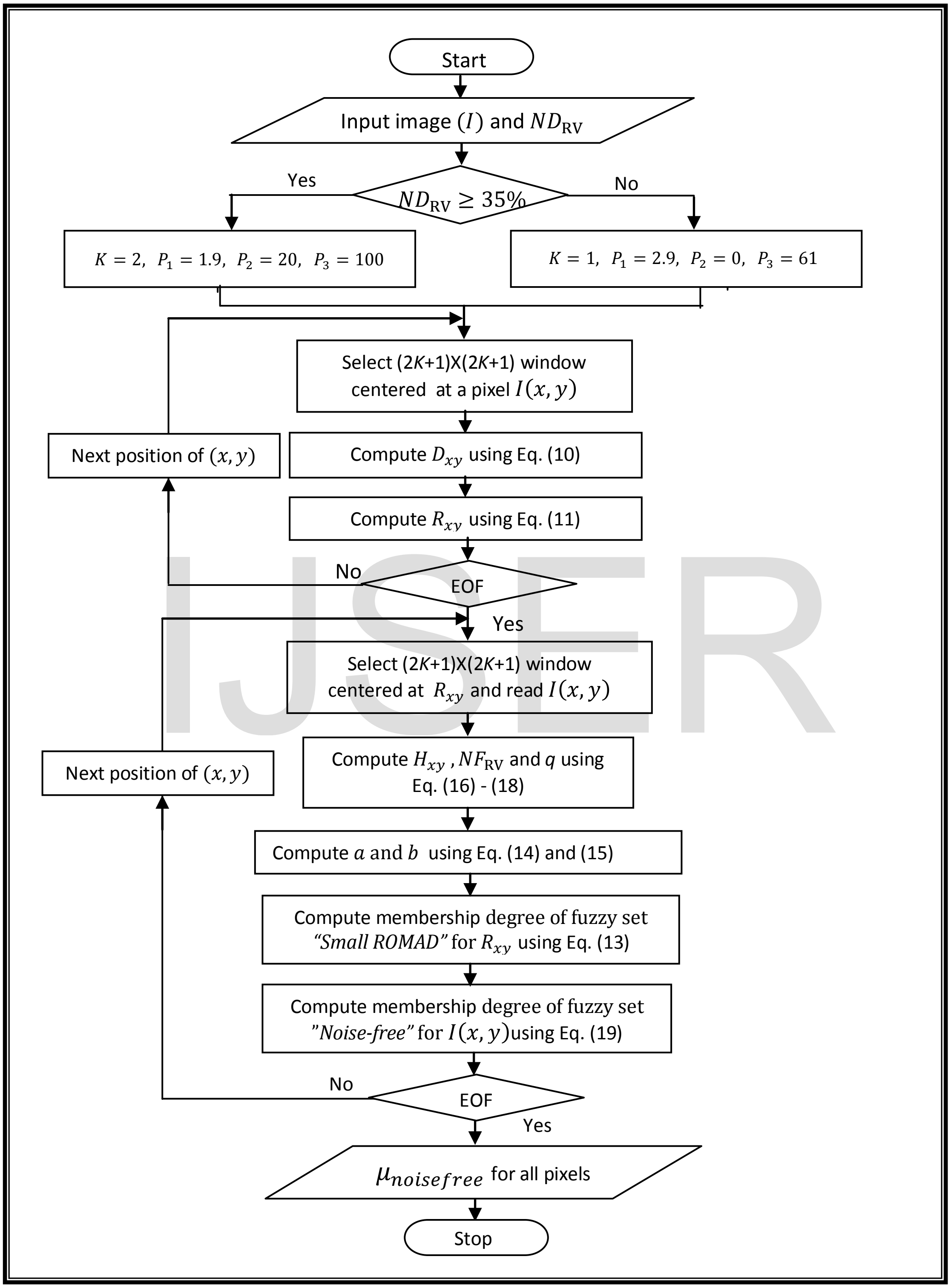

Fig. 3 Flowchart of RVIN detection steps

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4 Noise Filtering

The filtering process operates on only those pixels that have a membership degree smaller than one in the fuzzy set Noise-Free (i.e.,$\mu_{noisefree}(I(x,y)) < 1$ is considered as a noisy pixel). The filtering window size $(2L+1)\times(2L+1)$ is chosen adaptively according to the output of noise detection step (i.e., $\mu_{noisefree}$) as follows:

1- count the number of the noise free pixels in that window by:

$$G_{xy}^{f} = \sum_{s=-L}^{L}\sum_{t=-L}^{L} I(x+s,y+t) \; with \; \mu_{noisefree}\big(I(x+s,y+t)\big) = 1 \qquad \ldots(20)$$

2- If $(G_{xy}^{f} < 1)$, then the window size will be increased by incrementing the value of L. This procedure is repeated until the condition $(G_{xy}^{f} \geq 1)$ is met.

When the pixels in a neighborhood are similar or belong to very homogeneous region, median based algorithms are working well in removal of impulse noise, but when the pixels are belong to region that contains an edges or image details, it is necessary to incorporate the knowledge of the other pixels which is represented by their weights. Hence, for each observed filtering window $(2L+1)\times(2L+1)$ a fuzzy set called *"Similar"* is constructed for determining the similarity degree of each pixel in that window as well as to the weight that assigned in the noise detection step. Pixels having similar intensities in the observed filtering window will have higher membership degree in fuzzy set Similar. Edge pixels also will have similar intensities along the edges hence will have higher membership degree, whereas noisy pixels will have dissimilar intensities from neighboring pixels hence their membership degree will be low. The fuzzy set *"Similar"* is represented by Gaussian shaped fuzzy membership function $\mu_{similar}$ as shown in Fig. 4 .

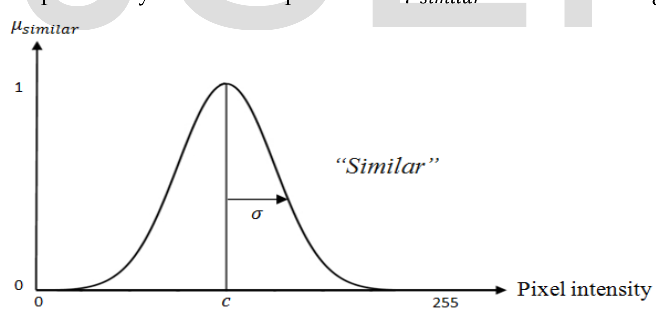

Fig. 4 Membership function similar of fuzzy set *"Similar"*

The membership function of fuzzy set *"Similar "*is determined by two parameters (c and σ). Where c represents the center of the membership function (i.e., where the membership function achieves a maximum value), and σ is related to the spread of the membership function. Hence, these parameters are derived adaptively according to the neighborhood homogeneity at $(2L+1)\times(2L+1)$ as follows:

$$c = \underset{-L\leq s,t\leq L}{\text{mean}}\big(I(x+s,y+t)\big), \quad \text{with } \mu_{noisefree} I(x+s,y+t) = 1 \qquad \ldots(21)$$

$$\sigma = \max\Big(\underset{-L\leq s,t\leq L}{\text{mean}}\big(|I(x+s,y+t)-c|\big), 0.01\Big) \qquad \ldots(22)$$

The behavior of the membership function $\mu_{similar}$ can be described depending on Eq. (21) and (22) as follows:

1- The spread of the membership function will be relatively large when the observed window belong to non-homogenous region (e.g., at edges or image texture). Whereas the spread of the membership function will be decreased whenever the homogeneity level will be increased. In the exceptional case when the noise free pixels in the observed window have the same value, the value of σ will be zero (the output is infinity). Therefore, the Max operation in Eq.(22) is used with (0.01) to avoid the infinity case in Eq.(23).
2- The membership function achieves a maximum degree at the mean value of the noise free pixels in the observed window.

Hence, the efficiency of the filtering process will be increased with employing the membership function $\mu_{similar}$ by removing noisy pixels and keeping image details intact as much as possible. The membership function $\mu_{similar}$ is given by [10]:

$$\mu_{similar}(I(x,y)) = e^{-\left(\frac{I(x,y)-c}{2\sigma}\right)^2} \quad \ldots (23)$$

The final fuzzy weight w_k for each pixel p_k in the observed window of size $(2L+1)\times(2L+1)$ is determined by the following fuzzy rule:

Fuzzy Rule 2: Defining the fuzzy weight degree for $\boldsymbol{p_k}$:
IF ($\boldsymbol{p_k}$ is noise-free) AND ($\boldsymbol{p_k}$ is similar)
THEN ($\boldsymbol{w_k}$ is high)

This rule can be implemented using the intersection operation of two fuzzy sets. Thus, the truthness of the rule 2 is obtained by:

$$w_k = min\{\mu_{noisefree}(p_k), \mu_{\boldsymbol{similar}}(p_k)\} \quad \ldots (24)$$

Where, the index k varies from 1 to $(2L+1)^2$ to select one of the window elements.
Ultimately, the output of the fuzzy filtering process for a certain pixel $I(x,y)$ in the considered window of size $(2L+1)\times(2L+1)$ is denoted as $F(x,y)$ and is calculated as follows [9]:

$$F(x,y) = (1-w(x,y) \times \frac{\sum_{s=-L}^{L}\sum_{t=-L}^{L} I(x+s,y+t).w(x+s,y+t)}{\sum_{s=-L}^{L}\sum_{t=-L}^{L} w(x+s,y+t)} + w(x,y).I(x,y) \quad \ldots(25)$$

Where, $I(x+s,y+t)$ represents the pixels of the considered window around the central pixel and $w(x+s,y+t)$ represents the corresponding weight for each pixel in that window.

5 Procedure for Iterations

In noise detection step, the membership function μ_{small} as shown in Fig. 1 adapts its shape according to the estimated noise density. Hence, the proposed method is applied iteratively with two iterations to remove higher amount of noise without degraded image details. The second iteration uses the modified image that result after the first iteration.

6 EXPERIMENTAL RESULTS

In this section, the performance of the proposed method will be compared with various well-known noise reduction methods by using the well-known test images: "Parrot" and "boats" with size of 256X256. The objective quantitative measures used for comparison are:

1- The peak signal to noise ratio (PSNR) which is one of the most common measures of image quality which measures the similarity between two images. The higher the PSNR value is, the more similar are the two images. The PSNR is defined as [8]:

$$PSNR = 10\, log_{10}\left(\frac{255^2}{MSE}\right) \qquad ...(26)$$

Where MSE is the mean square error and given by:

$$MSE = \frac{\sum_{x=1}^{M}\sum_{y=1}^{N}(O(x,y) - F(X,Y))^2}{M \times N} \qquad ...(27)$$

2- The edge measure (β) which expresses the edge preservation strength of the filtering method. The value of β should be close to one for an optimal effect of edge preservation. The parameter β can be calculated by[11]:

$$\beta = \frac{\sum_{x=1}^{M}\sum_{y=1}^{N}(\Delta O(x,y) - \bar{O})(\Delta F(x,y) - \bar{F})}{\sqrt{\left[\sum_{x=1}^{M}\sum_{y=1}^{N}(\Delta O(x,y) - \bar{O})^2\right]\left[\sum_{x=1}^{M}\sum_{y=1}^{N}(\Delta F(x,y) - \bar{F})^2\right]}} \qquad ...(28)$$

Where, ΔO and ΔF are the high-pass filter of O and F respectively, and $\bar{O}$ and $\bar{F}$ are the mean of ΔO and ΔF respectively. The high-pass filter is obtained in this work with standard approximation of sobel operator. The sobel operator is detailed in [12].

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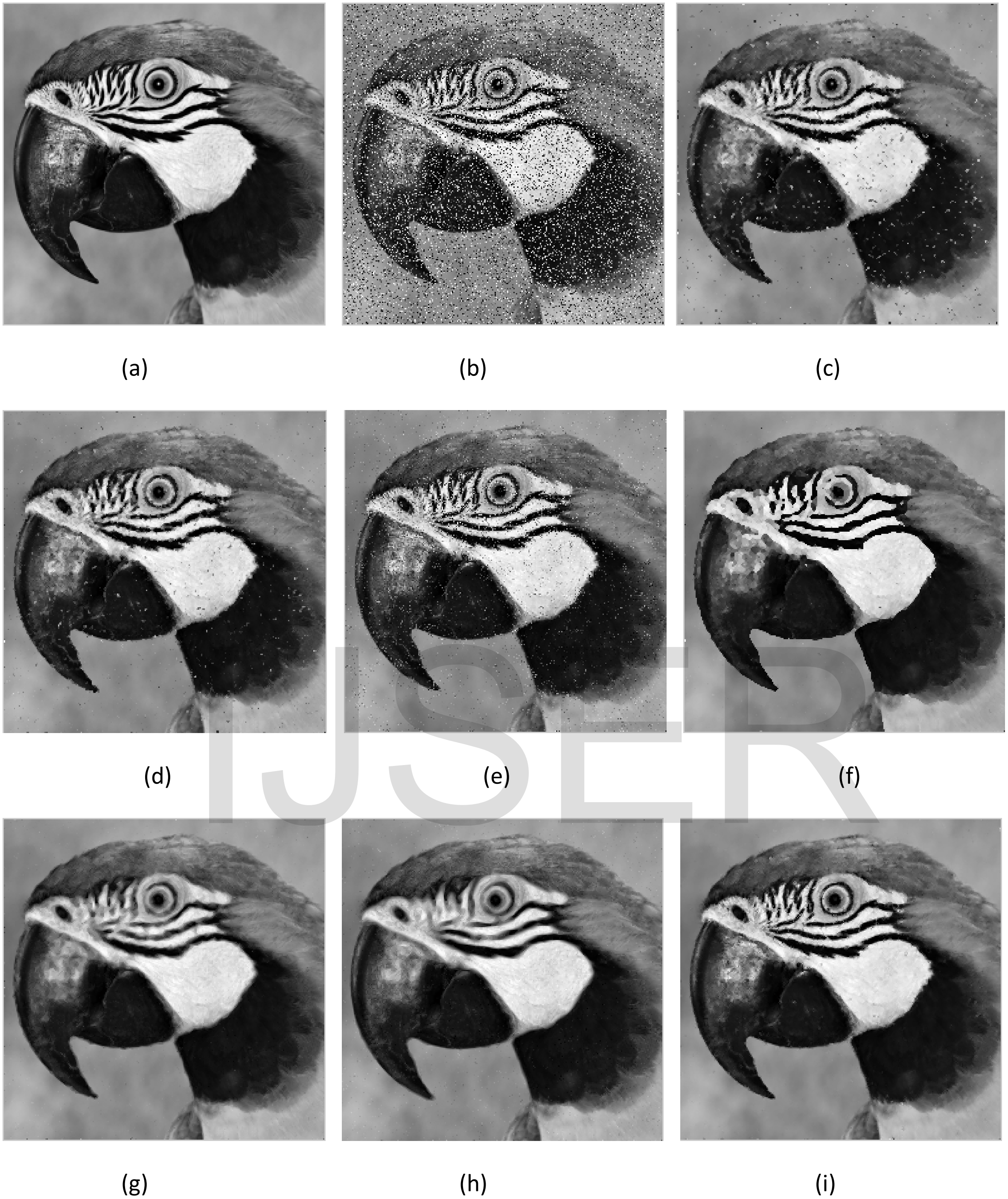

Fig. 6: Results of RVIN reduction of “Parrot” image, (a) original image, (b) Noisy image corrupted with 25 % RVIN (PSNR: 14.17), (c) Filtered image using CWM (PSNR: 23.73), (d) Filtered image using ACWM (PSNR: 24.66), (e) Filtered image using DWMFF (PSNR: 22.61), (f) Filtered image using CAFSM (PSNR: 22.36), (g) Filtered image using SOD-DWM (PSNR: 23.57) (h) Filtered image using DWM (PSNR: 23.53), (i) Filtered image using the proposed method (PSNR: 27.05).

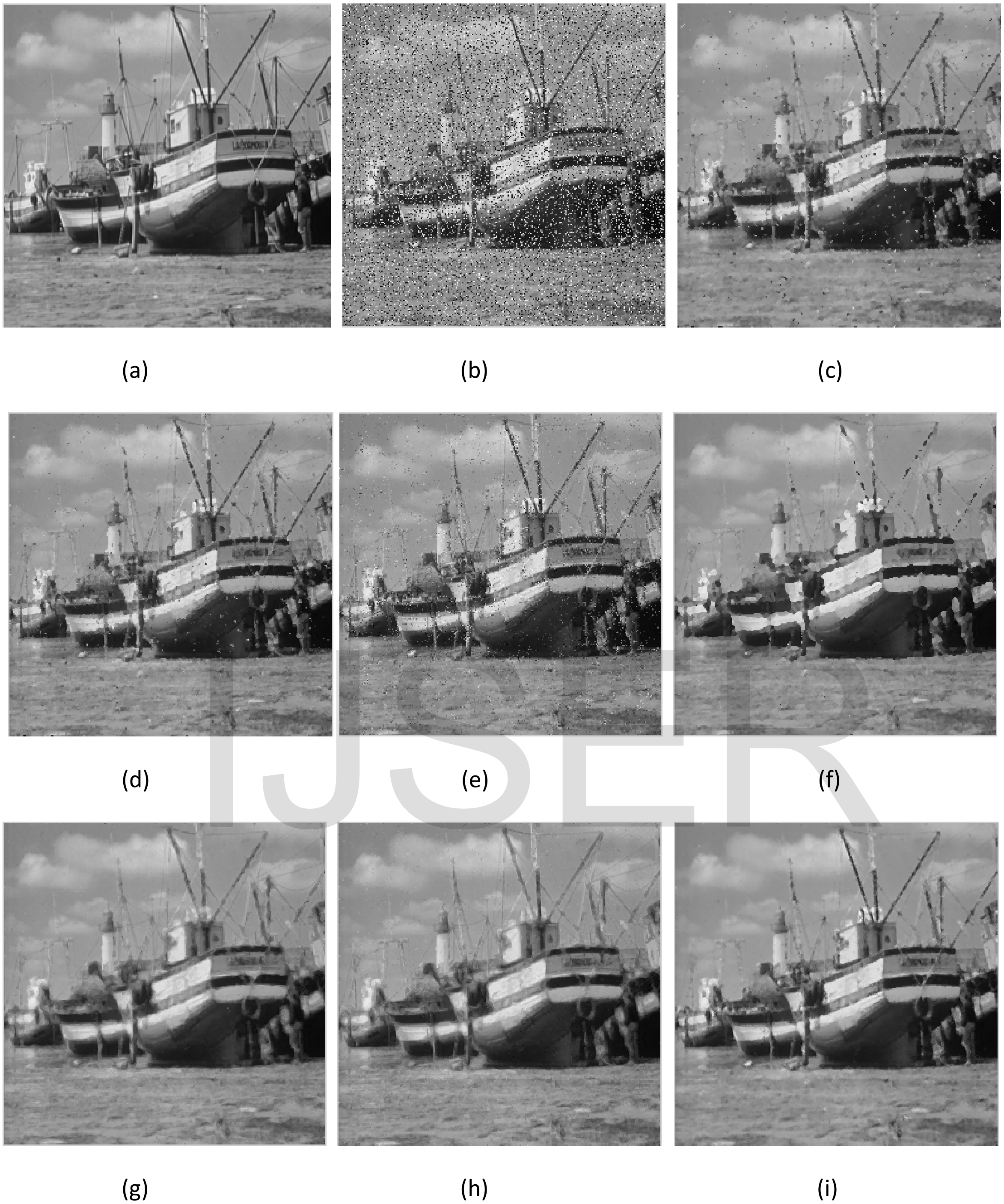

Fig. 5: Results of RVIN reduction of "Boats" image, (a) original image, (b) Noisy image corrupted with 25 % RVIN (PSNR: 15.33), (c) Filtered image using CWM (PSNR: 25.67), (d) Filtered image using ACWM (PSNR: 26.79), (e) Filtered image using DWMFF (PSNR: 24.21), (f) Filtered image using CAFSM (PSNR: 24.58), (g) Filtered image using SOD-DWM (PSNR: 26.35) (h) Filtered image using DWM (PSNR: 26.38), (i) Filtered image using the proposed method (PSNR: 28.50).

Table (2) shows the numerical results of objective quality measurements in terms of PSNR and the edge measure for the "Parrot", "boats", "cameraman" and "baboon" images corrupted with wide range of RVIN (10% - 50%). This table indicates that the proposed method outperforms the other filtering methods. Additionally, these results are visually confirmed in Fig. 5 and Fig. 6 that show the noisy the "Parrot" and "boats" images corrupted with 25% RVIN and the filtered image for all of the compared methods. It can be observed from these figures that the proposed method has butter performance in noise suppression and detail preservation as compared with other methods.

Table 2 Comparative results in PSNR and β of the proposed method with the related works using the "cameraman" and "baboon" images corrupted with RVIN.

Image	Method	10%		20%		30%		40%		50%	
		PSNR	β	PSNR	β	PSNR	β	PSNR	β	PSNR	β
Parrot	Noisy	18.02	0.5756	15.03	0.4069	13.35	0.2905	12.07	0.1926	11.13	0.1355
	CWM	28.83	0.7961	25.66	0.6923	22.17	0.5453	18.98	0.3691	16.77	0.2288
	ACWM	28.64	0.7683	25.97	0.6766	23.39	0.5585	20.21	0.3586	17.84	0.2376
	CAFSM	22.65	0.5455	22.66	0.5508	22.25	0.5114	21.28	0.4653	20.06	0.3776
	DWMFF	28.06	0.7909	24.51	0.6946	20.80	0.5553	17.18	0.3992	14.45	0.2480
	SOD-DWM	25.45	0.6382	24.39	0.5553	23.42	0.4981	21.85	0.4036	20.59	0.3078
	DWM	25.94	0.6955	24.43	0.5947	23.56	0.5407	22.48	0.4493	21.38	0.3815
	FRINDR	30.92	0.8628	28.16	0.7804	26.36	0.6887	23.87	0.5793	22.46	0.4666
Boats	Noisy	19.26	0.4100	16.40	0.2426	14.61	0.1384	13.32	0.0694	12.37	0.0403
	CWM	30.00	0.7249	27.35	0.6397	24.15	0.4739	21.54	0.3004	19.23	0.1685
	ACWM	30.52	0.7334	28.14	0.6420	25.54	0.5294	22.82	0.3718	20.45	0.2219
	CAFSM	25.06	0.4842	24.77	0.4556	24.09	0.4228	23.43	0.3525	22.29	0.3029
	DWMFF	29.06	0.7308	26.23	0.6605	22.48	0.5141	18.92	0.3163	16.09	0.1647
	SOD-DWM	27.68	0.5396	26.58	0.4735	25.97	0.4257	24.96	0.3332	23.76	0.2858
	DWM	28.89	0.6578	26.84	0.5128	25.99	0.4425	25.18	0.3855	24.34	0.3221
	FRINDR	32.42	0.8476	29.74	0.7311	27.48	0.5823	25.86	0.4512	24.80	0.3854
Camera-man	Noisy	18.32	0.5136	15.37	0.3267	13.63	0.2020	12.37	0.1153	11.41	0.0663
	CWM	29.61	0.7658	25.96	0.6436	22.55	0.4872	19.54	0.3210	17.27	0.1910
	ACWM	29.81	0.7602	27.35	0.6535	24.13	0.5221	21.22	0.3528	18.51	0.2177
	CAFSM	24.40	0.5522	24.10	0.5195	23.54	0.4832	22.79	0.4196	21.94	0.3857
	DWMFF	28.84	0.7594	26.03	0.6965	21.88	0.5520	18.10	0.3711	15.04	0.2308
	SOD-DWM	26.97	0.5993	26.13	0.5553	25.13	0.4633	24.04	0.3782	22.53	0.2966
	DWM	27.38	0.6786	26.21	0.5881	25.12	0.5080	24.53	0.4517	23.39	0.3669
	FRINDR	32.01	0.8698	29.36	0.7709	27.39	0.6563	25.53	0.5566	24.08	0.4470
Baboon	Noisy	19.63	0.2836	16.69	0.1248	14.97	0.0714	13.72	0.0468	12.73	0.0229
	CWM	26.98	0.5596	25.22	0.4411	23.33	0.3142	21.09	0.2052	19.31	0.0983
	ACWM	27.32	0.5621	26.00	0.4940	24.33	0.3887	22.30	0.2782	20.44	0.1695
	CAFSM	24.27	0.3813	23.74	0.3342	23.04	0.2786	22.01	0.2273	21.01	0.1690
	DWMFF	28.43	0.6706	25.30	0.5866	21.70	0.3714	18.53	0.1934	15.98	0.0948
	SOD-DWM	25.11	0.3714	24.54	0.3021	24.04	0.2692	23.47	0.2204	22.61	0.1648
	DWM	27.73	0.5644	25.61	0.3906	24.45	0.2983	23.81	0.2507	22.97	0.1802
	FRINDR	28.94	0.6869	26.46	0.5122	25.12	0.3811	24.14	0.3116	23.21	0.2068

7 Conclusion

In this paper, a new fuzzy random impulse noise detection and reduction (FRINDR) method based on fuzzy logic and noise density estimation is introduced. The proposed method employs the estimated noise density to select an appropriate window size used in noise detection step and also to determine the shape of the membership function used in noise detection step. Experimental results show that the proposed method outperform many existing impulse noise reduction methods in both subjective and objective measurements. Additionally, it can remove noise while preserving image details and textures very well.

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