Generalization of Impulse Noise Removal

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Abstract: *In this paper, a generalization for the identification and removal of an impulse noise is proposed. To remove the salt-and-pepper noise an Improved Directional Weighted Median Filter (IDWMF) is proposed. Number of optimal direction are proposed to increase from four to eight directions to preserve the edges and to identify the noise, effectively. Modified Switching Median Filter (MSMF) is proposed to replace the identified noisy pixel. In which, two special cases are considered to replace the identified noisy pixel. To remove the random-valued impulse noise, we have proposed an efficient random-valued impulse noise identifier and removal algorithm named as Local Noise Identifier and Multi-Texton Removal (LNI-MTR). We have proposed to use the local statistics of four neighbouring and the central pixel for the identification of noisy pixel in current sliding window. The pixel identified as noisy, is proposed to replace by using the information of multi-texton in current sliding window. Experimental results show that the proposed methods cannot only identify the impulse noise efficiently, but also can preserve the detailed information of an image.*

Keywords: *Directional weighted median filter, multi-texton, impulse noise, random-valued impulse noise, salt-and-pepper noise, noise identification, modified switching median filter.*

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1. Introduction

Impulse noise is very common to appear during the acquisition or transmission of an image. Impulse noise can be categorized into two types; it can be fixed-valued, such as Salt-and-Pepper impulse Noise (SPN), or random-valued, such as Random-Valued Impulse Noise (RVIN) [8]. SPN can corrupt the images, where the corrupted pixel takes either minimum or maximum gray level (0 or 255). However in RVIN, noisy pixels can have a value ranging from 0 to 255. Numerous non-linear methods were proposed to remove impulse noise [1-31].

Median Filter (MF) is known as the easiest, most common and popular non-linear filter used for impulse noise removal [22]. In MF, each pixel value is replaced by the median value of sliding window. However, for salient regions, MF cause blurred and distorted feature. Adaptive Median Filter (AMF) was proposed [17] to overcome the aforementioned problem of MF. In AMF, the window size increases repeatedly until it finds a non-noisy pixel as median or it reaches to the maximum window size. The major drawback of AMF is, it increases the computation cost for high-intensity noise [17].

In order to overcome the drawback of MF, many filtering algorithms including an impulse detector have been proposed, such as Tri-State Median (TSM) filter [9], Weighted Median Filter (WMF) [27], the Pixel-wise Median Absolute Difference (PWMAD) filter [10], Center-Weighted Median (CWM) filter [19] and Adaptive Center-Weighted Median filter (ACWM) [6] emphasize on the central pixel, and can smooth slightly corrupted images in a better way, however, for heavily corrupted images it is not significantly better than that of MF [22]. All the filters listed above are spatially invariant to operators, which make no distinction between noisy and noise-free pixels.

Switching Median (SM) filter was proposed to preserve the edges of an object [25]. The main idea of the SM is to use an impulse detector before filtering. This detector is based on a prior threshold value in order to decide whether a median filter can be applied or not. The disadvantage of SM was the need of prior threshold, which is not an easy task to be determined.

In order to overcome the problem of SM, Adaptive Switching Median (ASWM) filter was proposed to remove impulse noise from corrupted images [2]. In ASWM, unlike a classical SM filter, there is no need of prior threshold. Instead, threshold is locally computed from image pixels intensity values in a sliding window.

Decision-based Algorithm (DBA) was proposed that acts like a trimmed median filter. In case, whenever the algorithm cannot detect a non-noisy pixel, it uses the last processed pixel as a substitute of current pixel [24]. However, it cannot perform better because propagation can cause blurring. Wang *et al.* proposed a New Impulse Detection (NID) and filtering method that was based on the minimum absolute value of four convolutions obtained by one-dimensional Laplacian operators [28]. NID performs well on the images having many edges, but there still remains a need to set up threshold value manually

A New Approach (NA) was proposed by [18], which uses the modified mean filter to suppress the detected noisy pixels. Each pixel in the noisy image is considered as an original pixel and is compared with the chosen threshold values to identify whether the pixel is noisy or noise-free. The selected thresholds are based on the features of the impulse noise. It is better to determine the threshold on low-intensity impulse noise. However, for high-intensity impulse noise, adaptive threshold may not identify the impulse noise accurately.

Fast and Efficient Median Filter (FEMF) has proposed by [16] for removal of impulse noise, in which median filter uses prior information to capture natural pixels for restoration. Depending on different noise ratios of an image, two different sets of masked pixels are employed separately for the adoption of candidates for median finding. Furthermore, no limit to the size of mask windows assures that a proper median can be found. At high-intensity impulse noise, no limitation to the size of mask window increases the computational cost as well as leads to replace the corrupted image pixel again with noisy pixel value. A new method SDTF has proposed to eliminate the impulse noise by [31]. Based on the characteristic of noise, three kinds of basic noise patterns are proposed, which are used to identify the noise candidates. Simultaneously, noise removal operators are presented to remove the impulse noise.

An Adaptive Median-based Lifting (AML) filter for image de-noising was proposed by [23] to remove the impulse noise of an image corrupted by homogeneous SPN. The median based lifting filter removes the noise of the input image by calculating the median of the neighboring significant pixels. Esakkirajan *et al.* has proposed a method named as Modified Decision Based Unsymmetric Trimmed Median Filter (MDBUTMF) [15] to replace the noisy pixel by trimming median filter for obtaining the high-intensity impulse, however, it fails to produce better results as it uses average value to replace the noisy pixel value.

A Directional Weighted-median (DWM) filter was proposed to remove RVIN [14]. This method evaluates the neighbor's information of the central pixel in four directions to weight the pixels in a local window. A noise-corrupted pixel could be identified, and hence be removed by the weighted median filter in the optimal direction. After impulse noise identification, it does not simply replace noisy pixels identified by the outputs of median filter. While removing the noise, in order to preserve the details it continues to use the information of the four directions to weight the pixels in the window [14]. For the edge detection, they just consider the horizontal, vertical and two diagonal directions, which can only cater the edge information in these four directions. Identified noisy pixel is replaced with median value in optimal direction. For high-intensity impulse noise, it is possible that the median value obtained in an optimal direction is again a noisy pixel value. Thusly, the problem of DWM needs to be investigated further.

For SPN, an Improved Directional Weighted Median Filter (IDWMF) is proposed to solve the problem to correctly identify the edges, salient regions, and the noisy pixels. Pixels identified as noisy pixel is replaced with an appropriate pixel value in a more effective way by propose Modified Switching Median Filter (MSMF). This is done by finding a better edge direction from eight instead of four directions and also by giving it an additional constraint on performing SMF.

For RVIN, we have proposed to estimate the threshold value to identify the central pixel in sliding window as noisy or noise free by using the local statistics of the central pixel with four adjacent pixels to the central pixel. Estimated threshold value is used to define the threshold value range to identify the noisy and noise free pixels by adding and subtracting some small constant value. In order to replace the noisy pixel value, we have proposed four special types of texton in the current sliding window to estimating the best pixel value.

The contributions of our work are as follows:

For SPN:

1) No of optimal directions are increased from four to eight to correctly identify the noise in an optimal direction
2) Two cases are considered to modify the SMF for the replacement of noisy pixel.

For RVIN:

1) Proposal of local threshold value range based on local statistics to identify the current pixel as noisy or noise free
2) Multi-texton based noise removal method is proposed.

The rest of this paper is organized as follows. The background knowledge is given in section 2. Section 3 describes the proposed methods for removing impulse noise. Section 4 shows the experimental results. Conclusions are finally drawn in section 5.

2. Background Knowledge

In this section, we have given an overview of the DWM and SMF.

2.1. Directional Weighted Median

DWM filter was proposed for the removal of the random- valued impulse noise [14]. It was proposed to find the edge and the noisy pixel in four optimal directions. In which, one direction is horizontal, one is vertical and the other two directions are diagonal ones as shown in Figure 2-a. Finally, noisy pixel value is replaced with the standard MF [22].

2.2. Switching Median filter

SMF [1, 8, 12, 29, 30] are known to outperform standard median filters due to their capability of filtering candidate noisy pixels and leaving other pixels intact for the removal of impulse noise.

3. Proposed Method

Figure 1 shows the block diagram of the proposed method for the identification and removal of impulse noise. Each pixel in noisy image is analysed with proposed noise identifiers to check whether the current pixel in current sliding window is noisy or noise free. The pixel identified as noisy pixel is replaced with proposed noise removal methods and finally the noise free image is obtained.

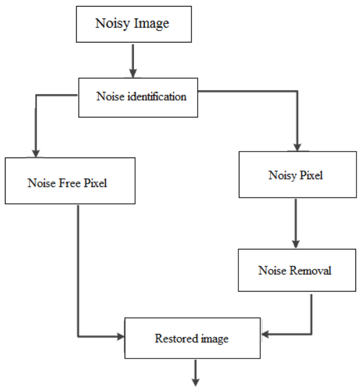


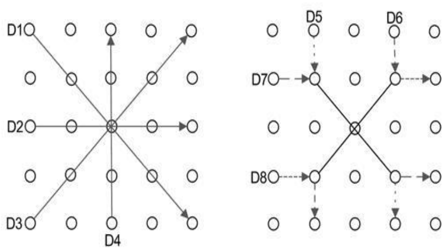
Figure 1. Block diagram of proposed method.

3.1.Proposed Method for Salt-and-Pepper Noise

IDWMF can be implemented in two stages: the first stage is to detect the noise in optimal direction, and the other is to remove the noise by using suitable values.

3.1.1. Salt-and-Pepper Noise Identification

An image is considered to be a noise free, if it contains the varying areas separated by edges in a local window smoothly. DWM filter was proposed to find the edges of an object in the four directions in the sliding window of 5 ˙ 5 [14]. To improve the edge detection in the local window, we proposed eight directions to find the edges of an object. The proposed strategy is shown in Figure 2.



a) Shows the 1st to 4th directions while. b) Shows the 5th to 8th directions.

Figure 2. The eight directions are used to detect the edges in an image.

For all the directions, we take the absolute difference between the current pixel with the neighbour's pixels in the optimal direction. For D_1 to D_4 in Figure 2, we use Equation 1 to calculate the absolute difference.

$$d_{i,j}^{k} = \sum_{\Delta i,\Delta j} w_{\Delta i\Delta j} \cdot \left| x_{i+\Delta i,j+\Delta j} - x_{i,j} \right| \tag{1}$$

Where k shows the direction index, that is $1 \leq k \geq 4$. $w_{\Delta i,\Delta j}$ is the weight of the neighbour pixel assigned using the Equation 2. If the difference between two adjacent pixels is very less, then in order to differentiate between the edges or smooth areas, it is needed to assign the larger weight to the pixels having less difference in the window. Considering the central pixel with adjacent pixel, if the edge of an object or the smooth varying area occurs then the grey value difference should be very close.

$$w_{\Delta i\Delta j} = \begin{cases} 2 & -1 \leq \Delta i, \Delta j \geq 1 \\ 1 & otherwise \end{cases} \tag{2}$$

The coordinates of direction D_5 to D_8 are shown in Equation 3.

$$\begin{aligned} D_5 &= \{(-1,2),(-1,1),(0,0),(1,-1),(2,-2)\} \\ D_6 &= \{(1,2),(1,1),(0,0),(-1,-1),(-1,-2)\} \\ D_7 &= \{(-2,1),(-1,-1),(0,0),(1,-1),(2,-1)\} \\ D_8 &= \{(-2,-1),(-1,-1),(0,0),(1,1),(1,2)\}. \end{aligned} \tag{3}$$

For d^5 to d^8, we can have the absolute difference from the indexes direction as shown in Equation 3. After computing the eight directions, we have to detect the edge of an object in the current window. So, we select the minimum absolute difference value among the eight directions. That optimal direction can be achieved and is given by Equation 4.

$$X = arg\,min\left\{d_{i,j}^{k} 1 \leq k \leq 8\right\} \tag{4}$$

In order to classify a pixel as noisy or noise free in the current window, the smallest value among the eight directions is used. If the difference value is small, it is considered to be a noise free pixel having a flat variation region or the edge of an object. Otherwise it is considered as a noisy pixel. We can classify noisy and noise free pixel by using Equation 5.

$$I = \begin{cases} nois\ free\ pixel & X \leq T \\ noisy\ pixel & otherwise \end{cases} \tag{5}$$

Where T is the threshold value to identify the central pixel as noisy or noise-free. T plays an important rule to identify the impulse noise; there is no hard and fast rule to determine the value of T. As it has been observed that for 8-bits gray-level images [14], the following selection of the threshold always yields to satisfactory results, that is

$$T_{n+1} = T_n * 0.8. \tag{6}$$

Where n≥0 shows the number of iterations. T_0 is chosen to be 510 for initial threshold. The range for the number of iteration is five to ten.

3.1.2.Modified Switching Median filter (MSMF)

After the identification of an impulse noise, it is needed to replace the noisy pixel value with the appropriate pixel value. SM filter is used to restore the value of the central pixel in the block [30]**.** The central pixel value is computed by Equation 7.

$$restored - pixel = \alpha_{ij} x_{ij} + \left(1 - \alpha_{ij}\right) x'_{ij} \,, \tag{7}$$

Where α_{ij} is a flag determined by the value of optimal direction. α_{ij} can only have two values {0, 1}. If the value of α_{ij} is 1, the central pixel is classified as an impulse free pixel. On the contrary, if the value of α_{ij} is 0 then the center pixel is classified as noisy pixel. Substituting the value of α_{ij} into Equation 7, the pixel would be restored according to the cases defined as below.

- *Case 1*. In order to improve the performance of the median filter for removing the impulse noise, we eliminate the minimum and maximum values (0 and 255) from the optimal direction. After eliminating the minimum and maximum values in the optimal direction, the median of the remaining values is used to replace the central pixel value.

$$x'_{ij} \,, \{x_{block} \neq 0 \quad and \quad x_{block} \neq 255\}. \tag{8}$$

- *Case 2*. For high-intensity noise values, one may encounter with special case, where all the values in optimal direction would be 0 or 255, here we proposed to calculate the mean instead of median value of the current optimal direction.

Algorithm 1: for IDWMF
Input: Noisy image
Output: Noise free image
1. Divide Image in 5 × 5 sliding window.
2. Compute the d^1 to d^8 by using Equation 1 and Equation 3.
3. Determine the minimum value from all d^1 to d^8 by using Equation 4.
4. Determine the noisy or noise free pixel by using Equation.
5. If central pixel is identified as noisy then replace it by MSMF.

3.2. Proposed Method for Random-Valued Impulse Noise (RVIN)

Proposed algorithm is divided into two stages: the first stage is to identify the noise by local statistics of current sliding window, while the second stage is to remove the noise by utilizing multi-texton method. LNI-MTR has a good trade-off between quantitative and qualitative properties of recovered images and the computational time. Section 3.2.1 shows the proposed method to identify the RVIN in detail and section 3.2.2 shows the proposed method to remove the noise using multi-texton.

3.2.1. Noise Identification

In sliding window, there is not much variation between the image pixel values. There is a strong correlation between the neighboring pixels in the sliding window. So the pixels have no correlation with neighboring pixels in the current sliding window must be treated as an outlier, which is considered as the noisy pixel.

We have proposed to identify a noisy pixel in an image by using the local statistics of sliding window to determine the threshold value range for each pixel in an image. Median value of four adjacent neighboring pixels with central pixel in current sliding window is proposed to estimate a threshold value. The coordinates of pixels used to estimate the threshold are as follows:

$$\begin{gathered} Thr = \{(1,2),(2,1),(2,2),(2,3),(3,2)\}, \\ Estimated\_value = median(Thr). \end{gathered} \tag{9}$$

Where Estimated_value is used to define the threshold value range to identify the noisy or noise free pixel.

Threshold values range is defined by adding and subtracting the constant value to the median value of sliding window. If the central pixel value of the sliding window lies between the threshold values range and it is identified as noise free otherwise it is considered as a noisy pixel. Number of experiments are conducted on standard images used for impulse noise removal to determine the best constant value used to define the threshold value range and '5' is found as best integer to define the upper and lower limit rage of threshold value range.

In proposed noise identification algorithm 3 × 3 sliding window is found better than other size of windows like 5 × 5 and 7 × 7. Figure 3 shows a real data example of one sliding window from the Lena image to identify the central pixel in sliding window as noisy or noise free. Matrix Original contains the real pixel values of one sliding window of Lena image and matrix $with_{noises}$. Shows the same sliding window pixel values after contaminated with the RVIN.

$$Original = \begin{pmatrix} 158 & 158 & 159 \\ 158 & 158 & 159 \\ 156 & 155 & 156 \end{pmatrix}$$

$$with_{noise} = \begin{pmatrix} 158 & 158 & 159 \\ 158 & 168 & 159 \\ 145 & 155 & 156 \end{pmatrix}$$

$$median(158,158,158,159,168) = 158,$$

Figure 3. Matrix termed as original is the one 3 × 3 sliding window of Lena image, while matrix termed as $with_{noise}$ have RVIN to identify the central pixel as the noisy or noise free pixel.

Median is calculated to define the threshold value range to identify the central pixel in sliding window as noisy or noise free. From Figure 3, it is clear that the lower limit of the threshold range is 153 (158-5) while the upper limit threshold range is 163 (158+5). It can be seen that the current pixel value does not lie between the defined threshold range, so the current pixel is identified as noisy pixel.

3.2.2. Noise Removal using Multi-texton

Correct replacement of pixel identified as noisy pixel also plays an important role. For the noise removal similarity based multi-texton algorithm is proposed. Multi-texton are used to find the edges of the objects in effective way. Considering the central pixel of 3 ˙ 3 sliding window in an image to be identified as noisy pixel, we have proposed four special type of texton, which can preserve the edges of an image as shown in Figure 4. We have named the proposed texton as T_1, T_2, T_3 and T_4. The coordinates of all proposed four textons are as follows:

$$T_1 = \{(1,1),(1,2),(2,1)\}, T_2 = \{(1,2),(1,3),(2,3)\},$$
$$T_3 = \{(2,1),(3,1),(3,2)\}, T_4 = \{(2,3),(3,2),(3,3)\}.$$

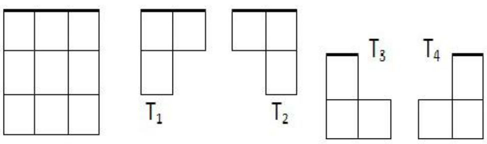


Figure 4. 3 ´ 3 Block of an image and the four propose textons to replace the noisy pixel value.

We have proposed to compute the absolute inner differences of all the four texton. After computing the difference of each texton, we have proposed to sum the inner differences of each texton. The texton having the small inner difference is considered as noise free and also has the more similar attributes. Among the four textons, after summing the inner differences of each texton, the texton having the smallest sum of difference is found. Then for replacing the noisy pixel value, we use the median value of the texton having the smallest sum of difference. From the above example in Figure 3, we can see that we can get the minimum value of T_1 among all of the four textons. So, current noisy pixel is replaced with the median value of propose texton T_1.

Algorithm 2: for LNI-MTR
Input: Noisy image
Output: Noise free image
1. Divide Image in 3 ˙ 3 sliding window.
2. Compute the Estimate_value to define the threshold value range by using Equation 9.
3. Define the Threshold value range by adding and subtracting some constant value to Estimate value.
4. Determine the noisy or noise free pixel by using aforementioned threshold value range.
5: If central pixel is identified as noisy then replace it by proposed multi-texton, otherwise go for the next pixel.

4. Results and Discussion

In this section the details of dataset, evaluation criterion and results and discussion on SPN and RVIN are given.

4.1. Dataset and Evaluation Criterion

In this section, performance of the proposed methods is compared with state-of-the-art filtering methods for removing impulse noise and preserving the image details.

In our experiments, we have used standard benchmark test images used for impulse noise removal: “Lena”, “Boat”, and “Baboon”, have a size of 512×512, while “Cameraman”, “Girl” and “House”, have a size of 256×256.

Restoration results were quantitatively measured by Peak Signal-to-Noise Ratio (PSNR), which can be expressed as [5].

$$PSNR = 10.log_{10}\left(\frac{Max^2}{MSE}\right)dB, \tag{10}$$

Where max denotes the largest value of gray-level, which is 255 for an 8-bit gray-level image. The MSE represents mean-square-error between original and restored images. It is computed by:

$$MSE = \frac{1}{M \times N}\sum_{i=1}^{M}\sum_{j=1}^{N}(O-R)^2. \tag{11}$$

Where O is the original image and R is the restored image. M ˙ N is the size of the original and restored image.

4.2. Results and Discussion for SPN

We have tested our proposed method with some state-of-the-art algorithms, which have been proposed for the removal of SPN. The 5 ˙ 5 sliding window size is used for the proposed IDWMF, which is found to be the best size for the identification and the removal of noise in DWM [14].

Table 1 shows the PSNR results of the proposed IDWMF method with state-of-the-art nonlinear impulse de-noising methods (MF [22], AMF [17], DBA [24], DWM [14], NID [28], NA [18], FEMF [16], AML [23], MDBUTMF [15], and SDTF [31]) on the Lena image (512×512) with varying noise intensity from 10% to 90%. It is clear from Table 1 that, increasing the number of optimal directions from four to eight can preserve the edges, salient regions in better way and can identify the noisy pixel correctly. MSMF also provide better estimation of pixel, to replace the identified noisy pixel. For the different noise intensity levels IDWMF achieves better PSNR than MF [22], AMF [17], DBA [24], DWM [14], NID [28], NA [18], FEMF [16], AML [23], MDBUTMF [15], and SDTF [31].

To verify the effectiveness of IDWMF, Table 2 shows the PSNR comparison of IDWMF on the different standard benchmark images (Lena, Girl, Cameraman, Baboon, House and Boat) having 50% noise intensity with aforementioned methods, which makes IDWMF a suitable validate candidate. We can see that IDWMF also performs better for all images as compared to aforementioned methods and acquires much better PSNR for high-intensity impulse noise.

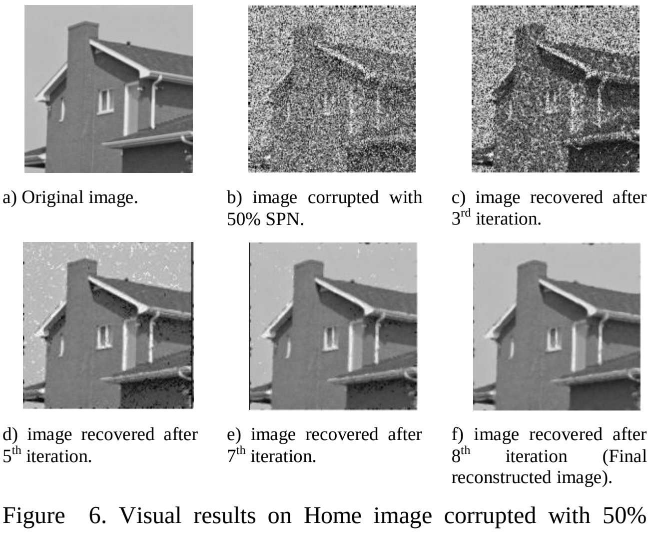
Table 1. Comparison of PSNR (dB) of different methods for the Lena image (512 × 512) at different SPN.

Noise %	MF	AMF	DBA	NID	MDBUTMF	SDTF	AML	FEMF	NA	DWM	IDWMF
10	26.34	28.43	36.4	38.2	37.51	38.14	39.04	39.15	39.21	40.7	42.06
20	25.66	27.4	32.9	34.32	34.78	35.28	36.25	36.45	36.22	37.02	39.45
30	21.86	26.11	30.15	32	32.29	33.94	33.61	34.31	34.29	34.56	37.12
40	18.21	24.4	28.49	30.27	30.32	32.38	32.98	33.13	32.98	32.36	35.36
50	15.04	23.36	26.41	28.04	28.18	29.51	31.67	31.28	31.85	30.75	32.93
60	11.08	20.6	24.83	27.33	26.23	27.23	28.14	29.64	30.82	27.63	31.87
70	9.93	15.25	22.64	25.03	24.3	26.79	26.22	27.18	27.13	25.23	29.35
80	8.68	10.31	20.32	23.3	21.4	23.42	23.78	23.47	24.18	21.9	27.59
90	6.3	7.34	16.43	21.36	18.4	22.23	22.2	22.94	23.02	15.8	23.43

Table 2. Comparison of PSNR (dB) values of different test images at 50% SPN.

Noise %	MF	AMF	DBA	NID	MDBUTMF	SDTF	AML	FEMF	NA	DWM	IDWMF
Lena	15.04	23.36	26.41	28.04	28.18	29.51	31.67	31.28	31.85	30.75	32.93
Girl	18.09	19.94	19.12	20.34	21.32	22.34	24.18	24.42	23.57	23.37	25.78
Cameraman	9.46	13.93	20.84	21.3	22.52	23.45	22.83	23.18	23.38	22.87	24.19
Baboon	10.11	20.65	22.35	22.9	23.8	23.89	22.46	23.57	23.1	23.05	26.32
House	15.38	21.32	27.93	28.62	28.95	29.16	28.37	29.23	29.19	28.98	31.58
Boat	15.6	23.27	25.6	27.74	28.65	28.94	28.12	29.78	29.37	26.63	31.04

Figure 6 shows the iterative process to identify and remove the noisy pixel form the House image with 50% of SPN. We can see that IDWMF preserves the edges of an image in better way and have ability to correctly identify the noisy pixel and remove the noisy pixel with proposed MSMF in better way.

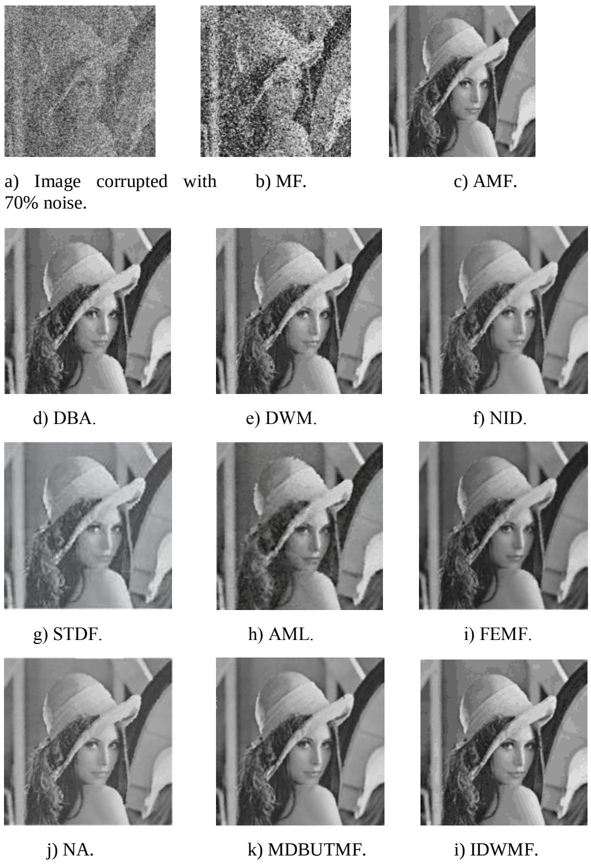


a) Original image. b) image corrupted with 50% SPN. c) image recovered after 3rd iteration.

d) image recovered after 5th iteration. e) image recovered after 7th iteration. f) image recovered after 8th iteration (Final reconstructed image).

Figure 6. Visual results on Home image corrupted with 50% impulse noise

Figure 7 shows the visual comparison of IDWMF with different methods MF [22], AMF [17], DBA [24], DWM [14], NID [28], NA [18], FEMF [16], AML [23], MDBUTMF [15], and SDTF [31] on the Lena image having 70% impulse noise. From the Figure 7, it is clear that in cases of high-intensity impulse noise, IDWMF performs much better than the aforementioned methods and preserves the edges of the objects in a superior way.



a) Image corrupted with 70% noise. b) MF. c) AMF.

d) DBA. e) DWM. f) NID.

g) STDF. h) AML. i) FEMF.

j) NA. k) MDBUTMF. i) IDWMF.

Figure 7. Image restoration results on the Lena image.

We have improved the results in a better way by increasing the number of directions for identifying the edges of objects in an image correctly, and also by adding two more constraints for modifying the SMF. For the high-intensity impulse noise MF [22], AMF [17], DBA [24], DWM [14], NID [28], NA [18], FEMF [16], AML [23], MDBUTMF [15], and SDTF [31] did not perform well. However, IDWMF performs better than the state-of-the-art methods such as [14, 15, 16, 17, 18, 22, 23, 24, 28, 31].

Eight directions for identifying the salient regions and smooth edges, make it able to replace the corrupted pixel values with the values originated from MSMF, so, the computational complexity of IDWMF is higher than DWM [14].

4.3. Results and Discussion for RVIN

For the validation of proposed LNI-MTR method, we have made the comparison with the state-of-the-art RVIN de-noising algorithms based on median value MF [22], AMF [17], DBA [24], DWM [18], ASWM [2]. Table 3 shows the PSNR obtained for different images having 30% RVIN. Results show that LNI-MTR performs better than other state-of-the-art methods in term of PSNR and also achieves the best image quality for RVIN.

Table 4 and 5 shows the PSNR results obtained for different images having 20% and 10% RVIN, respectively. It is clear that LNI-MTR performs better than other state-of-the-art methods proposed for RVIN removal.

Table 4. Comparison of PSNR (dB) values of different test images at 20% RVIN.

Method	MF	AMF	DBA	DWM	ASWM	LNI-MTR
Lena	18.83	27.57	31.38	35.63	36.51	38.81
Girl	21.73	23.32	25.71	26.83	27.17	38.87
Cameraman	14.39	19.57	21.83	26.35	27.55	29.35
Baboon	19.34	23.09	26.74	28.12	29.21	31.25
House	17.37	19.83	21.33	23.78	25.28	28.97
Boat	20.53	22.94	25.89	28.34	29.76	32.44

Table 5. Comparison of PSNR (dB) values of different test images at 10% RVIN.

Method	MF	AMF	DBA	DWM	ASWM	LNI-MTR
Lena	25.26	28.08	32.4	37.25	38.57	41.99
Girl	26.37	28.29	30.19	31.37	32.98	34.31
Cameraman	24.29	26.37	28.13	29.91	31.02	33.57
Baboon	22.89	24.63	28.54	29.16	30.94	32.52
House	23.37	25.77	28.73	29.32	30.94	32.52
Boat	22.04	24.58	27.35	30.5	31.38	33.2

LNI-MTR performs better because it preserves the edges of objects at the local level completely. By using the multi-texton for replacing the noisy pixel, gives the better estimation. The computational time of the LNI-MTR is also much lesser than that of AMF [17], DBA [24], DWM [14] and ASWM [2]. Initially, there is no need to define the threshold for the LNI-MTR like other methods [3, 14, 18, 20]. In propose method the block level threshold is changed for each pixel of the current sliding window that helps us to identify the noise correctly. LNI-MTR requires maximum three iterations while the previous methods require seven to ten iterations [2, 14, 18, 20], which also reduce the computational time of LNI-MTR method.

Figure 8 shows the visual result of the proposed LNI-MTR on Girl image with 30% RVIN. We can see that proposed noise identifier preserves the edges in better way and identify the noise correctly. Also proposed noise removal method estimates the best value to replace the noisy pixel.

a) Original image. b) image corrupted with 30% RVIN. c) Final reconstructed image(LNI-MTR).

Figure 8. Visual results on Girl image corrupted with 30% impulse noise

Figure 9 compares the visual results of different methods MF [22], AMF [17], DBA [24], DWM [14], ASWM [2] with LNI-MTR method on Lena image having 30% RVIN removal. It is clear from Figure 9, that the LNI-MTR also performs much better and preserve the edges of the objects in better way for RVIN. These results show that LNI-MTR exhibits better visual results because it has the capability to preserve the edges of an image by utilizing the special type of clique.

a) MF. b) AMF. c) DBA.

d) DWM. e) AWSM. f) LNI MTR.

Figure 9. Visual results on Lena image with 30% RVIN impulse noise.

In ASWM, the threshold determined form the local window is used to check whether the current pixel is noisy or noise free. However, in ASWM, all pixels of current block are used to determine the threshold value, which lead to wrong identification of impulse noise. We proposed to determine the threshold range in horizontal and vertical direction of the central pixel.

Then define the range instead of defining only one threshold value for determining the noisy pixel. For the removal of the noisy pixel, we have found the best neighboring pixel by using the proposed texton. In case, when only central pixel is corrupted by RVIN, we find more than one similar texton to replace the noisy pixel.

In DWM, without considering that the optimal direction has the noisy pixel, the identified noisy pixel is directly replaced with the median value of the pixels in the optimal direction. In multi-texton method, the chance of replacing the noisy pixel by another noisy pixel value is eliminated.

7. Conclusions

In this paper, a generalization of impulse noise identification and removal has been proposed. Proposed IDWMF for the identification and removal of SPN performs much better than others state-of-the-art image de-noising methods. Eight directions to identify the noise or edges of objects increased the identification of noisy or noise free pixel, correctly. Also proposed two cases to modify the SMF, Which can decrease the chance of incorrect replacement of noisy pixel. LNI-MTR outperforms over the state-of-the-art methods to identify and removal the RVIN. Adaptive threshold value is estimated by using the local statistics of neighboring pixels to identify the pixel noisy or noise free. Multi-texton method gives the best estimation of pixel to replace the noisy pixel. Experimental results show that for highly corrupted images based on well-known quantitative measure PSNR and visual quality, the proposed methods perform better than state-of-the-art filtering methods.

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