

# Image Transmission over Multipath Fading Channel and Image Denoising using Directional Weighted Median Filter

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## ABSTRACT

Impulse noise is often introduced into images during transmission contaminating the images due to channel errors. Based on the noise values, impulse noise can be classified as Fixed Valued Impulsive Noise or Salt and Pepper Noise (SPN) and Random Valued Impulsive Noise (RVIN). In this paper, an inpainting algorithm is presented based on Directional Weighted Median (DWM) Filter to denoise both the noises caused due to image transmission over multipath fading channel. The algorithm diffuses median value of pixels from the exterior area into the inner area and thus preserves the edges and fine details. The random valued impulsive noise and salt and pepper noise due to wireless channel modeled are simulated using MATLAB channel objects. The detection algorithm combined with the image correction based on DWMF shows better performance in terms of Peak Signal-to-Noise Ratio (PSNR) and Mean Absolute Error (MAE).

## General Terms

Image Reconstruction, Channel Fading

## Keywords

Inpainting, Random Valued Impulsive Noise (RVIN), Salt and Pepper Noise, Directional Weighted Median (DWM), PSNR, MAE.

## 1. INTRODUCTION

When image and video are transmitted over noisy channels, the data is either missing or incorrect due to channel transmission errors. As a result, impulse noise can appear because of a random bit error on a communication channel. The resulting two noises that corrupt the source images based on the noise value are:

- Salt and Pepper impulse Noise, which means a noisy pixel has a high value due to positive impulse noise and looks like white dot or snow in the image, or has a low value due to a negative impulse noise and looks like black dot or pepper in the image.
- Random Valued Impulse Noise can take any value that do not occur as extreme outliers in comparison with the surrounding pixels.

Nonlinear filters, which are based on statistical ordering of pixel values in a predefined fixed size sliding window, are effective in suppressing impulse noise in images. However, when they are applied to an image having uniformly distributed image values, undesired processing of noise-free pixels results in edge and texture blurring. The de-noising techniques based on median value works fine for restoring the images corrupted by Random Valued Impulse Noise with

low noise level but exhibits poor performance with highly corrupted images.

To achieve an optimal balance between signal-detail preservation and impulse noise attenuation, several works have been done to investigate impulse detector algorithms prior to noise removal techniques. These impulse detector techniques address the challenge of detecting noisy samples and selectively apply the result of noise removal techniques only to affected image regions. Many restoration algorithms have been proposed in the past to address the problem of filling in missing/corrupted data. Image Inpainting is one such technique which restores the damaged pixels in an undetectable form. Median based Inpainting technique diffuses the median of pixels which are exterior to inpainting area into the area to be inpainted. This technique is simple which achieves better results than other Inpainting techniques. Partial Differential Equation (PDE) based algorithms [1] are designed to connect edges and discontinuities and iteratively propagates information from outside of the area along isophotes. In convolution and filter based methods, inpainting is done by convolving the damaged image with a proper kernel. In this paper, Oliveira [2] proposed a fast digital image Inpainting method, which depends on convolution operation. This approach convolves regions to be inpainted with a diffusion mask repeatedly. However, convolution and filter based algorithms have good results only for images having no high contrast edges or high frequency components. When an image has high contrast edges or high frequency components, these algorithms produces some blurring in edge regions. In addition, the above techniques fail to recover the large regions containing the edges and are applied for the entire image. In the following paragraph, papers are referred for the purpose of studying median based techniques to restore the pixels damaged due to image transmission over fading channel.

A large number of algorithms have been proposed to remove impulse noise. In paper [3], starting from basics of median filter, the theory of Weight Median filtering and up to recently developed theory of optimal weighted median filtering for speech processing, adaptive weighted median and optimal weighted median filters for image and image sequence restoration, weighted medians as robust predictors in DEP coding and Quincunx coding is available. In paper [4], the directional median filter performs one-dimensional median filtering in the direction of the straight line component detected around the scratch. This method works effectively, even if a similar undamaged image area is not available. Among the works [5], [6], the median based filters are widely used because of their effective noise suppression capability and high computational efficiency. However, the

technique uniformly replaces the gray-level value of every pixel by the median of its neighbors in the sliding window. Consequently, some desirable details are also removed, in particular, when the window size is large. For the removal of random-valued impulse noise, a directional weighted median filters (DWM) [7] and Multi-stage Directional Median Filter (MSDWM) [8] provides a better solution. The filter [7] uses a new impulse detector, which is based on the difference between the current pixel and its neighbors aligned with four main directions. The algorithm is fast and provides good results in both edges and smooth regions. In this paper, an impulse detector, which exhibits better impulse detection capability than the others in combination with the output of the directional weighted median filter can suppress most noise while preserving more detail features and even thin lines. The method [8] can effectively restore images corrupted with Gaussian noise and mixed Gaussian and impulse noise. The method [9], replaces the damaged pixel by the median of the pixels in each direction. The technique is fast and iterative. It gives good performance even when noise level is high. A method [10] for removing film scratches in old video is proposed. The spacio-temporal inpainting restores scratch areas with image pixels in a similar undamaged image area in the same and the adjacent frames. The weighted median filtering method is selected and is used in this paper to eliminate both impulsive noises caused due to still image transmission over fading channel.

## 2. IMPULSE DETECTOR AND NOISE REMOVAL TECHNIQUES

When errors occur in the received image, the damaged pixel becomes inconsistent with its neighboring pixels which are received correctly. To decide whether a pixel is an erroneous one or not, properties like, the type of image, characteristics and density of noise are useful. This observation forms the basis of error detection of the damaged pixels. The proposed error detection method only makes use of the characteristics of the received image. It does not require additional information afforded by the encoder or channel. For the images which are corrupted by Salt and Pepper Noise, the error values of the images can take only the maximum and the minimum value in the dynamic range, the detection of noisy pixel in such case is simple. For the images which are corrupted by Random Valued Impulse Noise, detection of noisy pixel is more difficult in comparison with fixed valued impulse noise, as the gray level of noisy pixel may not be substantially larger or smaller than those of its neighbors. In such situations, noise removal is carried out with filtering which involves two steps. Noisy pixels are identified in the first step, and in the second step, it filters those noisy pixels. The following error detection and correction technique combination can be used for the removal of both RVIN and SPN.

### 2.1 Impulse Detector and Directional Weighted Median Filter

Solution to image restoration problem entirely depends on properties of image. In an contaminated image, the first difference between the error pixel and its neighboring pixel will result in change in gray level. Based on this, the discontinuities in an image can be used to model noise points. The sanctity of a pixel is decided solely by the threshold. If a predefined parameter of a test pixel exceeds the threshold value, it is termed as contaminated, otherwise not. A suitable error correction can be used to replace the identified damaged pixels. Therefore, the combination of error detection followed

by noise removal algorithm can be used to restore the essential pixel values.

A scheme is presented based on Directional Weighted Median (DWM) Filter to denoise both the image errors (RVIN and Salt and Pepper noise) caused due to image transmission over multipath fading channel. The DWM approach works in two phases. In the first phase, the contaminated pixel is detected by finding the absolute difference between the test pixel and its neighbor pixel aligned with the four main directions. During the second phase, the directional weighted median filter replaces only the corrupted pixels by its output and keeping the remaining intact.

Let  $x_{i,j}$  be the gray-level of a true  $M - by - N$  image  $X$  at a pixel location  $(i, j)$ , and  $[L_{min}, L_{max}]$  be the dynamic range of  $X$ , i.e.,  $L_{min} \leq x_{i,j} \leq L_{max}$  for all  $(i, j)$ .

Let  $Y$  be the noisy image. In the impulse noise model, the observed noisy gray level at pixel location  $(i, j)$  is observed as,

$$y_{i,j} = \begin{cases} n_{i,j}, & \text{with probability } p \\ x_{i,j}, & \text{with probability } 1 - p \end{cases} \quad (1)$$

Where,  $n_{i,j}$  is the noisy pixel at the pixel location  $(i, j)$ . When  $n_{i,j} \in [L_{min}, L_{max}]$ , the image is referred to be corrupted with Random Valued Impulsive Noise (RVIN) and when  $n_{i,j} \in \{L_{min}, L_{max}\}$ , then it is said to be Fixed Valued Impulsive Noise or Salt and Pepper Noise (SPN).

Before introducing the new impulse detector, it is assumed that, a local noise-free image consists of smoothly varying regions separated by edges. Here, the focus is on the edges aligned with four main directions as shown in Figure 1.

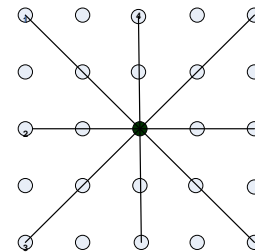


Fig 1. The four directions for impulse detection

Let  $S_k$  ( $k = 1$  to  $4$ ) denotes a set of coordinates aligned with the  $k^{\text{th}}$  direction centered at  $(0,0)$ . Each direction is explained by the set of coordinates as,

$$S_1 = \{(-2, -2), (-1, -1), (0,0), (1,1), (2,2)\},$$

$$S_2 = \{(0, -2), (0, -1), (0,0), (0,1), (0,2)\},$$

$$S_3 = \{(2, -2), (1, -1), (0,0), (-1,1), (-2,2)\}$$

$$S_4 = \{(-2,0), (-1,0), (0,0), (1,0), (2,0)\}.$$

Then, let  $S_k^0 = S_k \setminus (0,0)$  for all  $k$  from 1 to 4. For each direction, define  $d_{i,j}^{(k)}$  as the sum of all absolute differences of gray-level values between  $y_{i+s,j+t}$  and  $y_{i,j}$  with  $(s, t) \in S_k^0$ . Before the sum is calculated, the closest pixels to the center are weighted with 2 by considering the fact that, two pixels whose spatial distance is smaller than their gray-level values should be close. A  $5 \times 5$  window centered at  $(i, j)$ , for each direction, define  $d_{i,j}^{(k)}$  as the sum of absolute differences as,

$$d_{i,j}^{(k)} = \sum_{(s,t) \in S_k^0} w_{s,t} |y_{i+s,j+t} - y_{i,j}|, 1 \leq k \leq 4 \quad (2)$$

Where,

$$w_{s,t} = \begin{cases} 2 & (s, t) \in \Omega^3, \text{ and } \Omega^3 \{(s, t) : -1 \leq s, t \leq 1\} \\ 1 & \text{otherwise} \end{cases} \quad (3)$$

where,  $d_{i,j}^{(k)}$  is denoted as direction index and is sensitive to an edge in a different direction. For impulse detection, the minimum of the computed four sums is used, which is written as,

$$r_{i,j} = \min \{d_{i,j}^{(k)} : 1 \leq k \leq 4\} \quad (4)$$

The value of  $r_{i,j}$  for the following three cases can be defined as, (a) When the current pixel is a flat region pixel,  $r_{i,j}$  is small, because of the four small direction indices. (b) When the current pixel is an impulse,  $r_{i,j}$  is large, because at least one of direction index is small. (c) When the current pixel is an impulse,  $r_{i,j}$  is large, because of the four large direction indices. From the above analysis, the current pixel is identified as noisy pixel by employing a threshold T,

$$y_{i,j} \text{ is a } \begin{cases} \text{noisy pixel,} & \text{if } r_{i,j} \leq T \\ \text{noise - free pixel,} & \text{if } r_{i,j} > T \end{cases} \quad (5)$$

Therefore, a binary flag map is generated from the impulse detection procedure. In the resulting binary flag map, let  $f_{i,j}$  represents the flag value on position of (i,j). For each pixel  $y_{i,j}$ , if  $y_{i,j}$  = noisy pixel, set  $f_{i,j} = 1$ , otherwise,  $y_{i,j}$  is considered as a noise free pixel and for that set  $f_{i,j} = 0$ .

After impulse detection, the median based filter replaces the noisy pixel by median value in predefined window of appropriate size. In this technique, the output of the directional weighted median (DWM) filter is used to restore the damaged pixels. In the filter window, a standard deviation is computed to determine the similarity along all the directions which suggests a possible diagonal edge. The information derived from the four directions is used and calculate the standard deviation  $\sigma_{i,j}^{(k)}$  of gray levels for all  $y_{i+s,j+t}$  with  $(s, t) \in S_k^0$  ( $k = 1$  to  $4$ ), respectively. Let,

$$l_{i,j} = \operatorname{argmin}_k \{ \sigma_{i,j}^{(k)} : k = 1 \text{ to } 4 \} \quad (6)$$

Where, the operator  $\operatorname{argmin}$  determines the minimizer of a function.

Since standard deviation describes how tightly all the pixel values are clustered around the mean in the set of pixels,  $l_{i,j}$  shows that the four pixels in the window aligned with this direction are closest to each other. In order to keep the thin lines and edges intact, the center value should also be close to them. Therefore, proper weights are assigned to the pixels aligned with this direction. Then, the median value of pixels in filter window along the direction found from the previous computation is used to replace the center noisy pixel as the estimated value given by,

$$m_{i,j} = \operatorname{median} \{ \tilde{w}_{s,t} \diamond y_{i+s,j+t} : (s, t) \in \Omega^3 \} \quad (7)$$

Where,

$$\tilde{w}_{s,t} = \begin{cases} 2, & (s, t) \in S_{l_{i,j}}^0 \\ 1 & \text{otherwise} \end{cases} \quad (8)$$

and the operator  $\diamond$  denotes repetition operation. Now with all above notations, it can be written as,,

$$u_{i,j} = \alpha_{i,j} y_{i,j} + (1 - \alpha_{i,j}) m_{i,j} \quad (9)$$

Where,

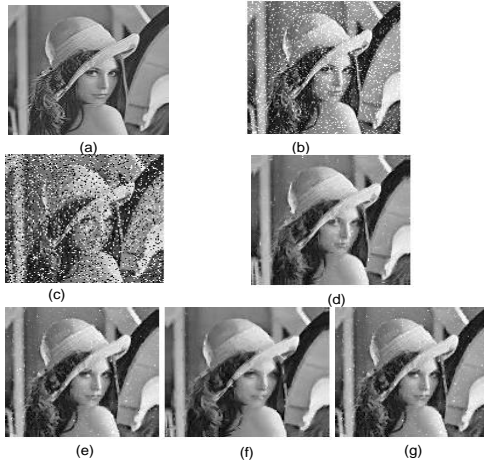
$$\alpha_{i,j} = \begin{cases} 0, & r_{i,j} > T \\ 1 & r_{i,j} \leq T \end{cases} \quad (10)$$

### 3. RESULTS AND DISCUSSION

Suppressing high Random Valued Impulsive Noise is far more difficult than suppressing fixed-valued impulse noise since for the latter, the differences in gray levels between noise-free neighbors and a noisy pixel are significant most of the times. In this paper, a Directional Weighted Median filter and conventional median based filter techniques have been employed to suppress both high random valued impulse noise (RVIN) and Fixed Value salt and pepper noise. To evaluate the performance of the method, extensive simulations are conducted on Lena and Mandril images. Finally, all the algorithms are implemented recursively, that is, the estimate of the current pixel is dependent on the previously processed pixels.

To carry out the simulations, the test images are corrupted by adding impulse noise to them. The images are corrupted at different noise densities. Two methods have been employed to generate the noise images. In the first method, the Fixed Value Impulse Noise (SPN) noisy images are generated by using built-in function (imnoise) and RVIN corrupted images are generated using MATLAB code (using 'randi' built-in function) for different noise densities. Here, the noise is usually quantified by the percentage of corrupted pixels. For example, if an image is corrupted by 30% impulse noise, then 15% of the pixels in the image may be corrupted by positive impulses and 15% of the pixels may be corrupted by negative impulses. In the impulse detection, the influence of the number of thresholds and the threshold values T are first investigated. Based on the heuristic approach, different threshold values are considered for the experimental simulations for each of the test image. In carrying out simulations, for the majority of test images, the most suitable threshold value employed by the filter is approximately T=60 and subsequently the threshold value is decreased by 5 for three to four iterations so that best results are obtained and larger PSNR values are achieved. In all simulations, a filtering window of 5x5 size slides from pixel to pixel in raster scanning fashion. Following this, the impulse noise images are corrected using conventional median based method and Directional Weighted Median method. Figure 2 illustrates the images of Lena for random valued impulse noise (RVIN) and Fixed Value salt and pepper noise introduced using 'imnoise' and 'randi' MATLAB functions and corrected images using conventional median based method and Directional Weighted Median method.

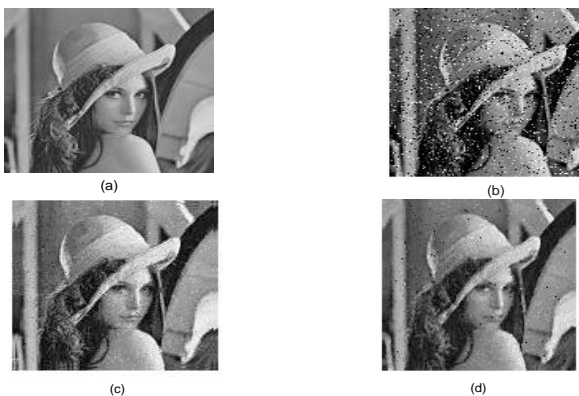
In the second method, instead of assuming random errors using built-in functions from MATLAB, the errors are simulated from wireless channel based on the Rayleigh model. A frequency-flat Rayleigh fading channel object is created using MATLAB. Table I show the property values that describe realistic fading channel (Rayleigh). The bit stream is modulated (DPSK modulation) and transmitted through Rayleigh fading channel. Damaged images received from the simulated wireless fading channel are interpreted as images corrupted by Random Valued Impulse Noise. Figure 3 illustrates the random valued impulse noise (RVIN) images of Lena due to channel errors and corrected images using conventional median based method and Directional Weighted Median method.



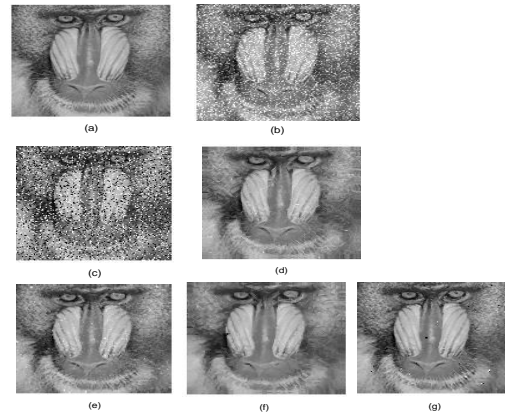
**Fig 2. (a) Original Lena Image. (b)Random Valued Impulse Noise (randi built-in function-MATLAB). (c) Salt and Pepper Noise (imnoise built- in function-MATLAB). (d) Restoration using DWM method (From RVIN Corrupted Image). (e) Restoration using Con.Median method (From RVIN Corrupted Image). (f) Restoration of using DWM method (From Salt and Pepper Noise Corrupted Image). (g) Restoration of using Con.Median method (From Salt and Pepper Noise Corrupted Image).**

**Table 1. Property values of Rayleigh channel**

Rayleigh channel	
ts, the sample time of the input signal	1e-3
fd, the maximum Doppler shift, in hertz	100
Path Delays in Secs	0 1e-5 1e- 5 1e-5 1e- 5 1e-4 1e- 4
Average Path Gain in dB	-6 -2 -5 -10 -8 -5 -10

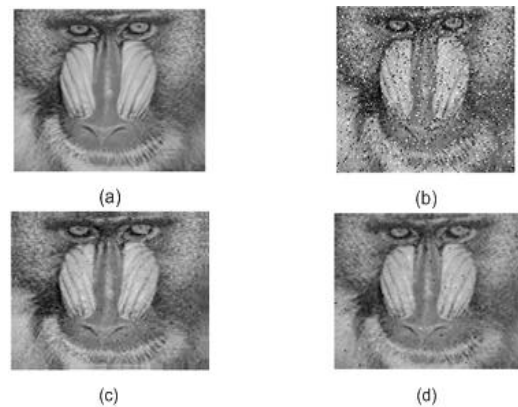


**Fig 3. (a)Original Lena Image. (b)Rayleigh channel received image.(c)Restoration using DWM method.(d)Restoration using Con.Median method.**



**Fig 4. (a) Original Mandril Image. (b)Random Valued Impulse Noise (randi built-in function-MATLAB). (c) Salt and Pepper Noise (imnoise built- in function-MATLAB). (d) Restoration using DWM method (From RVIN Corrupted Image). (e) Restoration using Con.Median method (From RVIN Corrupted Image). (f) Restoration of using DWM method (From Salt and Pepper Noise Corrupted Image). (g) Restoration of using Con.Median method (From Salt and Pepper Noise Corrupted Image).**

Mandril image is considered with the same noise effects as explained above. The restored images from DWM and conventional median algorithm are illustrated in Figure 4 and Figure 5.



**Fig 5. (a) Original Mandril Image. (b) Rayleigh channel received image. (c)Restoration using DWM method.(d)Restoration using Con.Median method.**

**Table 2. Comparison of restoration results in PSNR (dB) Lena Image (131x131 Size)**

Noise Level	RVIN DWM	RVIN SPN	RVIN Conv.Median	SPN Conv.Median
10%	2.5504	30.0250	32.9804	36.9526
20%	33.2068	28.2926	33.4322	31.7737
30%	33.3482	27.9185	34.5319	27.2160
40%	33.9955	26.0481	35.1777	22.9569
50%	34.8228	23.4756	36.4347	19.6487

**Table 3. Comparison of restoration results in PSNR (dB) Mandril Image (131x131 Size)**

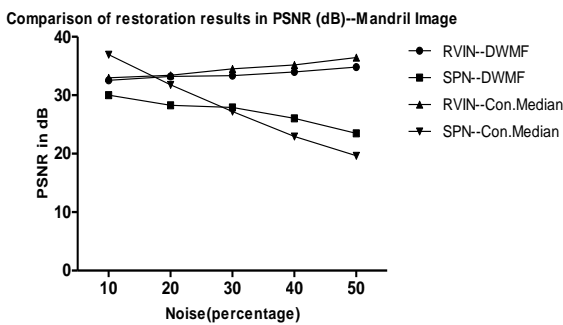
Noise Level	RVIN DWM	RVIN SPN	RVIN Conv.Median	SPN Conv.Median
10%	32.7906	30.0250	0 32.9804	4 36.9526
20%	32.7617	28.2926	33.4322	31.7737
30%	33.4588	27.9185	34.5319	27.2160
40%	33.6242	26.0481	35.1777	22.9569
50%	34.6844	23.4756	36.4347	19.6487

**Table 4. Comparison of restoration results in Mean Absolute Error (MAE) Lena Image (131x131 Size)**

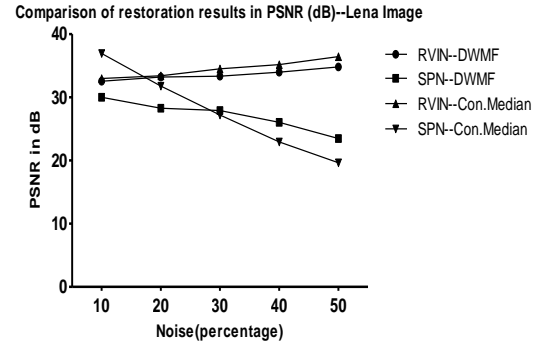
Noise Level	RVIN DWM	RVIN SPN	RVIN Conv.Median	SPN Conv.Median
10%	1.1990	2.1016	1.0085	0.4813
20%	1.3214	2.6293	0.9791	1.0630
30%	1.0617	3.1406	0.8132	1.9829
40%	0.8487	4.0424	0.7445	3.8860
50%	0.7790	5.5338	0.5996	6.7857

**Table 5. Comparison of restoration results in Mean Absolute Error (MAE) Mandril Image (131x131 Size)**

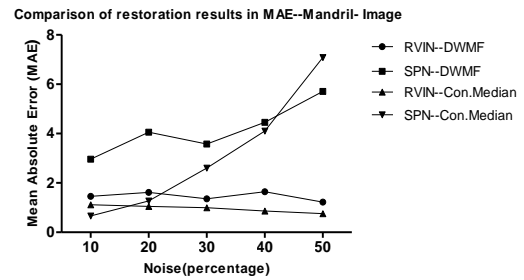
Noise Level	RVIN DWM	RVIN SPN	RVIN Conv.Median	SPN Conv.Median
10%	1.4589	2.9657	1.1199	0.6630
20%	1.6142	4.0582	2 1.0510	1.2718
30%	1.3539	3.5739	3 0.9934	2.6031
40%	1.6420	4.4593	0.8649	4.1059
50%	1.2241	5.7091	0.7590	7.0830



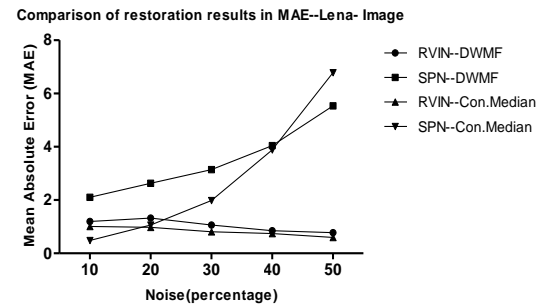
**Fig. 6. Restoration Results in PSNR (dB) for Lena Image**



**Fig.7. Restoration Results in PSNR (dB) for Lena Image**



**Fig. 8. Restoration Results in PSNR (dB) for Lena Image**



**Fig. 9. Restoration Results in PSNR (dB) for Lena Image**

The results DWM filter is compared with conventional median-based method for removal of SPN and RVIN images generated by various means. Figure 6, Figure 7, Figure 8 and Figure 9 shows the various simulation results for the Lena and Mandril images restored to indicate the performance of evaluation of DWM and conventional Median methods in terms of qualitative performance measures like PSNR in dB and MAE.

Restoration results are quantitatively measured by peak signal-to-noise ratio (PSNR) which is defined as,

$$PSNR = 10 \log \frac{\max_{(i,j) \in \mathcal{A}} (x_{i,j})^2}{\frac{1}{MN} \sum_{(i,j) \in \mathcal{A}} (u_{i,j} - x_{i,j})^2} \text{ (dB)} \quad (11)$$

where  $u_{i,j}$  and  $x_{i,j}$  denote the pixel values of the restored image and the original image respectively, and the image size is M-by-N with the coordinates (i, j) in the image domain  $\mathcal{A}$ .

Mean Absolute Error (MAE) is defined as,

$$MAE = \frac{1}{MN} \sum_{(i,j) \in \mathcal{A}} |u_{i,j} - x_{i,j}| \quad (12)$$

Table 4 and 5 show the various simulation results listed for the Lena and Mandril images corrupted using MATLAB built-in functions and restored to indicate the performance of evaluation of DWM and conventional Median methods in terms of MAE. It can be observed that some pixels are detected wrongly. The pixels detected wrongly are mainly those pixels that are in consistency with their neighboring pixels, and are even difficult to distinguish with human eyes. So, they will cause little effect on the following error correction. The results obtained from the simulations confirm the efficiency of the proposed method.

#### **4. CONCLUSION**

We have attempted to implement a new inpainting algorithm based on Directional Weighted Median filter. The proposed method uses the median of the pixels in a predefined size window in different directions to inpaint a damaged region. The algorithm is fast, simple to implement and provides adequate results in both smooth regions and high contrast edges. The algorithm is iterative and according to our experimental results, it converges at most in 2 or 3 iteration for simple damaged regions. For complex damaged image regions, a larger number of iterations will be required. It is also observed from the simulations that a single threshold value does not serve the purpose as well in different noise conditions. It can be concluded that an optimum threshold value may detect noisy pixels and the correction algorithm considered in the paper would provide very good results for all kind of images considered.

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