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Order Statistic Filters for removing Salt-and-Pepper Noise of Images: A Comparative Study

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Abstract— **The search for efficient noise removal methods from images is still a valid and serious challenge for the researchers. Clearing the noisy image is given the first priority before dealing with image processing algorithms on it. A plethora of existing algorithms are there and each of them has its assumptions, views, merits and demerits. All show an outstanding performance when the image model corresponds to the algorithm assumptions but fail in general and create artifacts or remove image fine structures. The paper lays focus on the review and comparative analysis of some important image noise removal techniques for reduction of impulse noise in time domain. This paper investigates a high-speed non-linear Order Statistic filter implementation as median filter. Then Adaptive Median Filter solves the dual purpose of removing the impulse noise from the image and reducing distortion in the image. The Adaptive Median Filtering can achieve the filtering operation of an image corrupted with impulse noise up to 60%.**

***Keywords*- multi-state median filter (msm); median filter, adaptive center-weighted median filter (acwm); directional weighted median filter (dwm);**

I. Introduction

The linear filters has poor performance in the presence of noise that is not additive. if a signal with sharp edges is corrupted by high frequency noise, however, in some noisy image data. The linear filters designed to remove the noise also smooth out signal edges. in addition, impulse noise can not be reduced sufficiently by linear filters. As already known, signals are not linear in nature. generally, when the filters are not linear, they show better performance than when they are linear in the removal of impulse noise from the image. The salt and pepper & random valued impulse noise occurs when the picture elements in the camera sensors do not function well or error in the memory location or during digitization process. a non linear scheme called median filtering with success in this situation. Order-statistic filters are nonlinear spatial filters whose response is based on ordering(ranking) the pixels contained in the image area encompassed by the filter, and then replacing the value of a centre pixel with the value determined by the ranking result. the best known filter in this category is the median filter, which , as its name implies, replaces the value of a pixel by the median of the intensity values in the neighbourhood of that pixel(the original value of the pixel is included in the computation of the median). Median filters are particularly effective in the presence of impulse noise, also called salt-and-pepper noise because of its appearance as white and black dots superimposed on an image[2].This paper lays emphasis on various techniques and methods of how to mitigate the noise. The capturing instruments, image quantization, data transmission media, and discrete sources of radiation exercise tremendous influence on the modelling of the noise in the images. On the basis of the noise model various algorithm are employed. a brief description of impulsive noise, Gaussian noise, and their combination (mixed noise) is mentioned with the model of each type as below.

II. TYPES OF NOISE

A. Impulsive Noise

Noise on a circuit that can be caused by voltage spikes in equipment, voltage changes on adjacent pairs in a copper cable, tones generated for network signaling, maintenance and test procedures, lightening flashes during thunderstorms, and a wide variety of other phenomena [1,2]. As impulse noise is short in duration (1 / 100 of a second, or so); it has little effect on voice communications, but can cause bit errors in a data transmission. Impulse noise, often found in digital transmission and storage, can be described by the following model:

$$I(t)=(1-e)\,S(t)+N(t) \tag{1}$$

$$where,\;\; e=\{0,1\}\; with\;\; a\;\; probability\;\; P.$$

$I(t)$ is the resulting data measured at time t, $S(t)$ is the original signal measured , and $N(t)$ is the noise introduced by the sampling process, environment and other source of interference.The PDF of(bipolar) impulse noise is given by[2] : **p**(z)=P_a for z=a, p(z)=P_b for z=b, p(z)=0 for otherwise, if b>a, intensity b will appear as a light dot in the image. Conversely , level a will appear like a dark dot. If either P_a or P_b is zero, the impulse noise is called unipolar. If neither probability is zero, and especially if they are approximately equal, impulse noise values will resemble salt-and- pepper granules randomly distributed over the image. For this reason, bipolar impulse noise also is called salt-and-pepper noise.

B. Gaussian Noise

In this type of noise, the image looks soft and slightly blurry, where each pixel in the image will be changed from its original value by a (usually) small amount. When we plot histogram, then the amount of distortion of a pixel value against the frequency, with which it occurs, shows a normal distribution of noise [1,2,5]. This type of noise is additive one. A pixel with co-ordinates (x, y) degraded by additive random noise is given which is modeled as,

$$f(x,y)=O(x,y)+\eta(x,y) \tag{2}$$

Where, $f(x,y)$ is final image function, $O(x,y)$ is orig inal image function and $\eta(x,y)$ represents the signal independent additive random noise.

The Gaussian noise has a normal (Gaussian) probability density function:

$$PDF_{\text{Gaussian}}=\frac{1}{\sqrt{2\pi\sigma^2}}\,e^{-\frac{(g-\mu)^2}{2\sigma^2}} \tag{3}$$

where, g=gray level, μ=mean, s=standard deviation.

C. Mixed Noise and Other types of Noises:

When more than one type of noise is present in the image, it is called mixed noise. In this type of noise, the image contains dark and white dots and looks soft and slightly blurry, where each pixel in the image is changed from its original value by a (usually) small amount [5].

Other types of noises are Rayleigh noise, Erlang(gamma) noise, Exponential noise, Uniform noise etc.

III. IMPULSE NOISE MODEL

noise can be classified as salt-and-pepper noise (SPN) and random-valued impulse noise (RVIN). An image containing impulsive noise can be described as follows:

$$x(i,j)=\begin{cases}\eta(i,j) \; with\; probability\;\; p\\ y(i,j)\;\; without\; probability\; 1-p\end{cases} \tag{4}$$

Where $x(i,j)$ denotes a noisy image pixel, $y(i,j)$ denotes a noise free image pixel and η(I,j) denotes a noisy impulse at the location (i,j). In salt-and-pepper noise, noisy pixels take either minimal or maximal values i.e. $\eta(i,j)\in\{L_{\min},L_{\max}\}$, and for random-valued impulse noise, noisy pixels take any value within the range minimal to maximal value i.e. $y(i,j)\in[L_{\min},L_{\max}]$ where $L_{\min},L_{\max}$ denote the lowest and the highest pixel luminance values within the dynamic range respectively. So that it is little bit difficult to remove random valued impulse noise rather than salt and pepper noise [3]. The main difficulties, which have to face for attenuation of noise, is the preservation of image details. Figure 3.1 may best describe the difference between SPN and RVIN. In the case of SPN the pixel substitute in the form of noise may be either Lmin(0) or Lmax(255). Where as, in RVIN situation it may range from Lmin to Lmax. Cleaning such noise is far more difficult than cleaning fixed-valued impulse noise since for the latter, the differences in gray levels between a noisy pixel and its noise-free neighbors are significant most of the times. In this thesis, we focus only on random valued impulse noise (RVIN) and schemes are proposed to suppress RVIN.

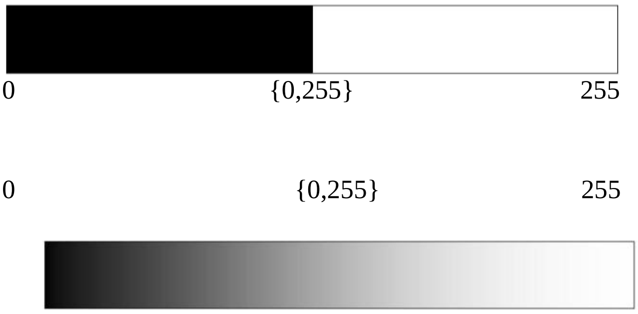


Figure 1: Representation of (a) Salt & Pepper Noise with $R_{i,j}\in\{n_{\min},n_{\max}\}$ (b)Random Valued Impulsive Noise with $R_{i,j}\in[n_{\min},n_{\max}]$

IV. PERFORMANCE MEASURES

A. Mean Squared Error (MSE) and Peak Signal to Noise Ratio (PSNR)

In statistics, the mean squared error or MSE of an estimator isone of many ways to quantify the amount by which an estimator differs from the true value of the quantity being estimated. Here it is just used to calculate the difference between a original image with a restored image. Given that original image Y of size $(M\times N)$ pixels and as reconstructed image $\hat{Y}$, the MSE(dB) is defined as:

$$MSE(dB)=\frac{1}{M\times N}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}\left(Y_{i,j}-\hat{Y}_{i,j}\right)^2 \tag{5}$$

PSNR analysis uses a standard mathematical model to measure an objective difference between two images. It estimates the quality of a reconstructed image with respect to an original image. Reconstructed images with higher PSNR are judged better [6]. Given that original image Y

of size $(M \times N)$ pixels and as reconstructed image $\hat{Y}$, the PSNR (dB) is defined as:

$$PSNR(dB) = 10\log_{10}\left(\frac{255^2}{\frac{1}{M \times N}\sum_{j=1}^{N}\left(Y_{i,j} - \hat{Y}_{i,j}\right)^2}\right) \quad (6)$$

B. Probability Density Function (PDF)

The PDF of (Bipolar) Impulse noise is given by,

$$p(z) = \begin{cases} p_a & for\ z = a \\ p_b & for\ z = b \\ 0 & otherwise \end{cases} \quad (7)$$

if b>a, gray-level **b** appears as a light dot in the image. Conversely, level **a** appears like a dark dot. If either p_a *or* p_b is zero, the impulse noise is called unipolar. If in any case, the probability is zero and especially if they are approximately equal, impulse noise values resemble Salt and Pepper granules randomly distributed over the image. For this reason, bipolar noise or impulse noise is also called Salt and Pepper (Shot and Spike) noise.

As a result, negative impulses appear as black (Pepper) points in an image. For the same reason positive impulses appear as white (Salt) noises. For an 8 bit image this means that a=0 (black) and b=255 (white).

C. Subjective or Qualitative measure

Along with the above performance measure subjective assessment is also required to measure the image quality. In a subjective assessment measures characteristics of human perception become paramount, and image quality is correlated with the preference of an observer or the performance of an operator for some specific task. However perceptual quality evaluation is not a deterministic process.

V. RECENT TRENDS OF RESEARCH IN NOISE REMOVAL OF DIGITAL IMAGES

The presence of noise in images is a common phenomenon. The removal of noise from the image is a difficult task in the image processing. The removal of high frequency impulsive noise by the use of median filters is widely accepted for image processing. As the median filters are nonlinear in character, they are better performers than any other filtering techniques in the removal of this type of noise [3]. Nevertheless, conventional filters do not produce expected result with the increasing occurrence of probability error. Recently, some adaptive median filtering algorithms have been developed in order to remove impulsive noise required for image processing applications.

The main challenge in research is to removal of impulsive noise as well as preserving the image details. Some schemes utilize detection of impulsive noise followed by filtering where as others filter without detection of noise. In the filtering without detection, a window mask is moved across the observed image. The mask is usually of size (2N +1)2 , where N is a positive integer. Generally the centre element is the pixel of interest. When the mask is moved starting from the left-top corner of the image to the right-bottom corner, it performs some arithmetical operations without discriminating any pixel. The disadvantage of this process is that it filters all the pixels irrespective of corruption. Detection followed by filtering involves two steps. In first step it identifies noisy pixels and in second step it filters those pixels. Here also a mask is moved across the image and some arithmetical operations are carried out to detect the noisy pixels. Then filtering operation is performed only on those pixels which are found to be noisy in the previous step, keeping the non-noisy intact. These filters, generally, consists of two steps. Detection of noisy pixels is followed by filtering. Filtering mechanism is applied only to the noisy pixels. Removal of the random-valued impulse noise is done by two stages: detection of noisy pixel and replacement of that pixel. Median filter is used as a backbone for removal of impulse noise. Many filters with an impulse detector are proposed to remove impulse noise.

The Median Filtering [2] Technique can successfully remove Impulse noise from the distorted image but in this case the filtered image suffers the blurring effect. For the median filtering techniques each pixel is considered to calculate the median and also every pixel is replaced by that calculated median. So affected pixels are considered to calculate the median and unaffected pixels are also replaced by this calculated median. This undesirable feature prevents the median filtering techniques from providing higher PSNR or better quality image.

The adaptive threshold median filter (ATMF) *[7]* is a combination of the adaptive median filter (AMF) and two dynamic thresholds & it manages to strike a balance between the removal of multiple impulse noise and the quality of image.

The *Improved Switching Median filter*[8*]* is effective to remove salt-and-pepper noise in images, although in case of uniformly distributed impulse noise, this method does not perform well.

The *Adaptive Center-Weighted Median Filter* (ACWM) [9] has devises a novel adaptive operator, which forms estimates based on the differences between the current pixel and the outputs of center-weighted median (CWM) filters with varied center weights. It employs the switching scheme based on the impulse detection mechanisms. It utilizes the center-weighted median filter that have varied center weights to define a more general operator, which realizes the impulse detection by using the differences defined between the outputs of CWM filters and the current pixel of concern. The ultimate output is switched between the median and the current pixel itself.

The *Multi-State Median Filter* (MSM) [10] has proposes a generalized framework of median based switching schemes, called multi-state median (MSM) filter. By using simple thresholding logic, the output of the MSM filter is adaptively switched among those of a group of center weighted median (CWM) filters that have different center weights. The MSM filter is equivalent to an adaptive CWM filter with a space varying center weight which is dependent on local signal statistics.

The *Tri-State Median Filter* (TSM) [11] has proposed for preserving image details while effectively suppressing impulse noise. It incorporates the standard median(SM) filter and the center weighted median (CWM) filter into a noise detection framework to determine whether a pixel is corrupted, before applying filtering unconditionally. Noise detection is realized by an impulse detector, which takes the outputs from the SM and CWM filters and compares them with the origin or center pixel value in order to make a tri-state decision. The switching logic is controlled by a threshold. The threshold affects the performance of impulse detection. An attractive merit of the TSM filter is that it provides an adaptive decision to detect local noise simply based on the outputs of these filters.

The *Advanced Impulse Detection Based on Pixel-Wise* MAD (PWMAD) [12] has a robust estimator of variance, MAD (median of the absolute deviations from the median), is modified and used to efficiently separate noisy pixels from the image details. The algorithm is free of varying parameters, requires no previous training or optimization, and successfully removes all type of impulse noise. The pixel-wise MAD concept is straightforward and low in complexity. The median of the absolute deviations from the median-MAD is used to estimate the presence of image details, thus providing their efficient separation from noisy image pixels. An iterative pixel-wise modification of MAD (PWMAD) provides reliable removal of arbitrarily distributed impulse noise.

The *Signal-Dependent Rank Order Mean* (SDROM) Filter [13] has a new framework for removing impulse noise from images, in which the nature of the filtering operation is conditioned on a state variable defined as the output of a classifier that operates on the differences between the input pixel and the remaining rank-ordered pixels in a sliding window. First, a simple two-state approach is described in which the algorithm switches between the output of an identity filter and a rank-ordered mean (ROM) filter. The technique achieves an excellent tradeoff between noise suppression and detail preservation with little increase in computational complexity over the simple median filter. For a small additional cost in memory, this simple strategy is easily generalized into a multi-state approach using weighted combinations of the identity and ROM filter in which the weighting coefficients can be optimized using image training data. Moreover, the method can effectively restore images corrupted with Gaussian noise and mixed Gaussian and impulse noise.

The *Directional Weighted Median Filter* (DWM) [14] has method is used for removal of random-valued impulse noise is directional weighted median filter (DWM). This filter uses a new impulse detector, which is based on the differences between the current pixel and its neighbours aligned with four main directions. After impulse detection, it does not simply replace noisy pixels identified by outputs of median filter but continue to use the information of the four directions to weight the pixels in the window in order to preserve the details as removing noise.

The *New Directional Weighted Median Filter* (NDWMF) uses a new impulse detector, which is based on the differences between the current pixel and its neighbours aligned with four main directions. First it considers a 5X5 window. Now, it considers the four directions: horizontal, vertical and two diagonal. Each direction there are 5 pixel points. It then calculates the weighted difference in each direction and takes the minimum of them. The minimum value is compared with a threshold value and if it is greater than the threshold value then it is a noisy pixel otherwise not.

In filtering phase, it calculates the standard deviation of grey level values of all pixels in four directions. Because the standard deviation describes how tightly all the values are clustered around the mean in the set of pixels shows that the four pixels aligned with this direction are the closest to each other. Therefore, the center value should also be close to them. Now it calculates the weighted median, giving extra weight on that direction in which direction standard deviation is small and replaces the noisy pixel with this median value. It is an iterative method. This method repeats 8 to 10 times. It gives the good performance when noise level is high too.

VI. SIMULATION AND RESULTS

Here, we have used the Matlab as a simulation software. The figure 2 shows the restored results of enlarged *Lena* image corrupted with 40% of RVIN (a)True image, (b) Noisy image, (c) Median Filtering, (d)ACWMF, (e) PWMAD, (f) SDROM, (g) DWMF, (h)NWDM. The figure-3 shows the performance comparison of different filtering methods graphically on image degraded by impulse noise at different noise level. Lena image corrupted with RVIN (10% to 60% of noise) is subjected to the different well known filtering schemes discussed above and their performance is measured using measurement metrics and the comparative results in PSNR (*dB*) of different filters are shown in table 1.

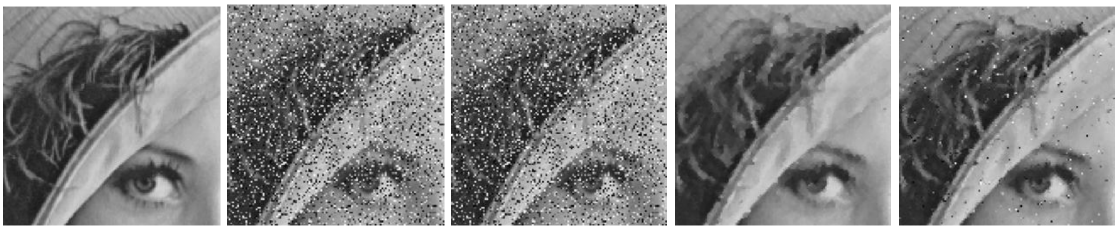
VII. DISCUSSION

The quantitative performance measures and visual quality of the images are taken into consideration to measure the performance of denoising algorithms. However, due to the varied nature and sources of noise, these assumptions may not hold true. An ideal denoising techniques calls for apriori knowledge of the noise. By observing Table 1, we can

conclude that The new directional weighted median filter (NDWMF) filter provides the better result in PSNR as compared to all other filters. The NDWMF filter only gives the better result in PSNR value when the noise is upto 40%. Performance of denoising algorithms is measured using quantitative performance measures such as peak signal-to-noise ratio (PSNR), signal-to-noise ratio (SNR) as well as in terms of visual quality of the images. Many of the current techniques assume the noise model to be Gaussian. In reality, this assumption may not always hold true due to the varied nature and sources of noise. An ideal denoising procedure requires *a priori* knowledge of the noise, whereas a practical procedure may not have the required information about the variance of the noise or the noise model. Thus, most of the algorithms assume known variance of the noise and the noise model to compare the performance with different algorithms.

TABLE 1: COMPARATIVE RESULTS IN PSNR(DB) OF DIFFERENT FILTERS FOR LENNA IMAGE CORRUPTED WITH RVIN

Name of the Image	Noise Level	Median Filtering	SD-ROM	ACWM	PWMAD	DWM	NWDM
Lenna.bmp (256 X 256)	10%	29.262	36.88	35.47	35.86	36.22	36.89
	20%	27.773	33.58	34.45	31.52	34.74	35.22
	30%	25.626	30.77	31.44	26.48	33.24	33.83
	40%	23.439	28.35	28.89	23.32	31.66	32.90
	50%	19.554	25.98	26.64	20.55	29.24	29.23
	60%	17.221	24.32	23.54	19.28	27.87	29.42



(a) (b) (c) (d)

(f) (g) (h)

Figure 2: Restored results of enlarged *Lena* image corrupted with 40% of RVIN (a)True image, (b) Noisy image, (c) Median Filtering, (d)ACWMF, (e) PWMAD, (f) SDROM, (g) DWMF, (h)NWDM

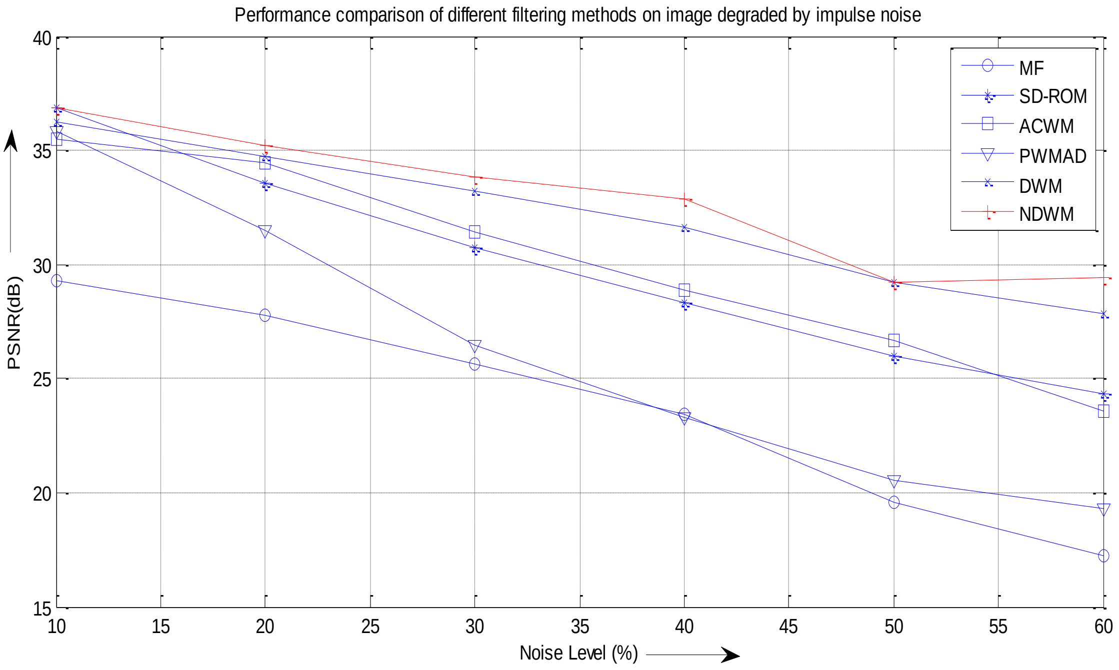


Fig.3 Performance comparison of different filtering methods on image degraded by impulse noise

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