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REMOVAL OF SALT AND PEPPER NOISE IN IMAGES USING WAVELET TRANSFORM AND MEDIAN FILTER

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ABSTRACT

In image processing, one of the major operations is image acquisition. If any Noise is entered during image acquisition may degrade the image quality and is difficult to remove the noise. For better noise removal in an image, non-linear filter is preferred rather than linear. This paper presents the use of Wavelet Transform and Median Filtering to remove Salt and Pepper Noise in Digital Images. In this paper first wavelet coefficients are calculated and then these coefficients are further modified by median filter. Proposed method provides better improvement over Gaussian noise for removing the noise from the image and provides good visual quality. In the wavelet decomposition three levels are used to find the coefficients and then applying the median filter over them. The performance is evaluated using Peak Signal to Noise Ratio (PSNR) and Root Mean Square Error (RMSE) and shows an improvement of image denoising over Gaussian method.

Keywords: Wavelet, noise, Median filter, PSNR and RMSE

I. INTRODUCTION

Impulse noise is caused by malfunctioning pixels in camera sensors, faulty memory locations in hardware, or transmission in a noisy channel (see [1], for instance). Two common types of impulse noise are the salt-and-pepper noise and the random-valued noise.Image restoration is preliminary track in image processing in current time. Image noising (distortion) is one of the well-known and a common issue in Image processing system. Image denoising operation is often used to denoise the degraded image. Image noising is generally seen due to various types of noise, for example Gaussian noise, Impulsive noise, Poisson noise and Speckle noise etc. These are fundamental noise types in case of digital images. Impulsive noise is completely removed by conventional median filter rather than other noise types. Impulsive noise is classified into Salt and Pepper noise and random valued noise [1].

In this paper, we use salt and pepper noise because it is most common and seen in general image processing operations. Noise is introduced in images during image acquisition or transmission or recording. This phenomenon may happen due to Electronic or photometric sources. If the image formation, transmission and reception processes in Electronic or photometric sources are imperfect, they produce blurred image. Image formation processes such as spreading of focal length, non-stationary camera placement cause bandwidth reduction in an image. Salt and pepper noise are generally caused by camera sensors, misaligned lenses and weak length of focal etc., [2].

That is why careful study of salt and pepper noise is essential which leads to proper selection of noise model for image denoising operations. Day by day the demand of the quality images is increasing. That is why the proposed scheme is to try to maintain the quality of visual perception of an image and also try to remove most of the noisy part in the degraded images.

Non-linear techniques have been proposed and used successfully for image denoising. However, traditional linear filtering does not perform well in case of non-linear operation of impulsive noise during image formation and transmission. An image signal has structural constraints, for examples lines, junctions, edges, corners and other fine details.

However most of linear filters have only low pass characteristics and hence edges, lines and other fine details are completely lost due to filtering [3-4]. Pixel based image denoising schemes are traditional and have been used for quite long time. In recent development, wavelet based image denoising algorithms have achieved remarkable results [5]. In this paper we propose wavelet transform of iterative noise density of salt and pepper noise and median filtering. However, instead of two fixed values, impulse noise can be more realistically modelled by two fixed ranges that appear at both ends. In the Boundary Discriminative Noise Detection (B +DND) is proposed to classify the pixels according to their intensities. The image restoration is done by using the switching median filter. A Noise Fading Technique (NFT) , presented in first applesian impulse detector and then employs a pixel restoring median filter for de noising the corrupted pixels in an iterative manner. In a Two-State Switching Median filter (TSSM) is proposed which uses a noise intensity identification scheme to detect the corrupted pixels. The filtering scheme is chosen from two different switching median filters [6-8].

A general model for impulse noise which assumes that impulses can take any subset of the entire grey-values dynamic range. Noisy pixels are detected based on iterative measuring the image entropy and restored using a Wavelet Transform Median filter (WTM). The proposed filter alters the corrupted pixels in a different number of iterations according to their Euclidean distance from the nearest uncorrupted pixel.

II. LITERATURE REVIEW

2.1 Restoration of Images by Using Fuzzy Technique

A novel data-dependent median filtering method is proposed [9] in order to restore images which are corrupted by 10-50% probability impulsive noise. Even if the image which is corrupted by high probability impulsive noise, the degree of impulsive noise is not uniform at each local window. Thus, the suitable window length is changed at each processed point. And if the processed point is not corrupted by impulsive noise, input signal should be not filtered in order to preserve signal details. From these points of view, the proposed filter combines median filters with a lot of different window sizes for preserving the signal details and removing impulsive noise perfectly**.** Median filter is useful for image restoring that are corrupted by impulsive noise. A lot of improvement methods about median filter are published. However, these methods can’t be useful for images that are corrupted by high-probability impulsive noise.

2.2. Hebbian Learning Based FIR Filter for Image Restoration

Image filtering techniques have potential applications in image processing such as image restoration and image enhancement. This makes the standard filters to be application specific. The widely used proximity based filters help in removing the noise by over-smoothing the edges. On the other hand, sharpening filters enhance the high frequency details making the image non-smooth. In this paper, we have introduced a new finite impulse response (FIR) filter for image restoration where, the filter undergoes a learning procedure. The FIR filter coefficients are adaptively updated based on correlated Hebbian learning [10]. This algorithm exploits the inter pixel correlation in the form of Hebbian learning and hence performs optimal smoothening of the noisy images. The proposed filter uses an iterative process for efficient learning from the neighborhood pixels. Evaluation result shows that the proposed FIR filter is an efficient filter compared to average and Wiener filters for image restoration applications.

Compared with conventional filters, the median filters and its variants are more robust in that a single very unrepresentative pixel in the filter window will not affect the median value significantly. In this paper, we have proposed a new algorithm based on Hebbian neural network learning scheme for the image restoration. This algorithm exploits the inter pixel correlation in order to optimally smoothen the image. The algorithm consists of two steps. First ,the FIR filtering step, which optimally filters the image. This is followed by the learning step, which updates the weight between two pixels based on the learning from neighborhood pixels.

2.3 Fast Directional Weighted Median Filter for Removal of Random-Valued Impulse Noise

The restoration process of many known median based algorithms is effective for the images corrupted by high random valued impulse noise, but not efficient especially for real-time applications. We proposed a new modus-operandi; by utilizing the competence of the fast median filter into modified Directional Weighted Median filter (DWM) [11], which can be used in real-time applications to remove random valued impulse noise efficiently and effectively from a highly corrupted image without conciliation on the result's excellence. The simulation fallout depict that the anticipated technique performs better, in terms of time complexity and PSNR, as compared to the existing methods as well as directional weighted median filter.

A strategy to efficiently compute the median by utilizing the competence of the fast median filter algorithms is into directional weighted median filter for random valued impulse noise. We have used the fast median filter, whose time complexity is almost linear as compared to the standard median filter which uses the efficient sorting algorithm to sort the pixel values, and then pick the middle value as median for that window.

2.4 Existing De-Noising Algorithm

An Impulse noise detection & removal with adaptive filtering approach is proposed to restore images corrupted by salt & pepper noise. The proposed algorithm works well for suppressing impulse noise with noise density from 5 to 60% while preserving image details. The difference of current central pixel with median of local neighborhood pixels is used to classify the central pixel as noisy or noise-free. The noise is attenuated by estimating the values of the noisy pixels with a switching based median filter applied exclusively to those neighborhood pixels not labeled as noisy. The size of filtering window is adaptive in nature and it depends on the number of noise-free pixels in current filtering window. Simulation results indicate that this filter is able to preserve 2-D edge structures of the image and delivers better performance with less computational complexity as compared to other demising algorithms existing in literature.

Mean Filtering: Mean filtering is a simple, intuitive and easy to implement method of smoothing images, i.e., reducing the amount of intensity variation between one pixel and the next. It is often used to reduce noise in images.

The idea of mean filtering is simply to replace each pixel value in an image with the mean ('average') value of its neighbors, including itself. This has the effect of eliminating pixel values which are unrepresentative of their surroundings. Mean filtering is usually thought of as a convolution filter. Like other convolutions it is based around a kernel, which represents the shape and size of the neighborhood to be sampled when calculating the mean. Often a 3*3 square kernel is used, although larger kernels (e.g.5*5 squares) can be used for more severe smoothing. (Note that a small kernel can be applied more than once in order to produce a similar but not identical effect as a single pass with a large kernel.)

This filter is also called as average filter. Generally speaking, this is the least satisfactory method of speckle noise reduction as it results in loss of detail and resolution. The Mean Filter is poor in edge preserving.

Median Filter: The median filter is a nonlinear digital filtering technique, often used to remove noise. Such noise reduction is a typical pre-processing step to improve the results of later processing (for example, edge detection on an image). Median filtering is very widely used in digital image processing because, under certain conditions, it preserves edges while removing noise.

The median Filter is performed by taking the magnitude of all of the vectors within a mask and sorted according to the magnitudes. The pixel with the magnitude is then used to replace the pixel studied. The Simple Median Filter has an advantage over the Mean filter since median of the data is taken instead of the mean of an image. The median of a set is more robust with respect to the presence of noise.

The main idea of the median filter is to run through the signal entry by entry, replacing each entry with the median of neighbouring entries. The pattern of neighbours is called “window”, which slides, entry by entry, over the entire signal. For ID signals, the most obvious window is just the first few preceding and following entries, whereas for 2D (or higher-dimensional) signals such as images, more complex window patterns are possible (such as “box” or “cross” patterns). Note that if the window has an odd number of entries, then the median is simple to define: it is just the middle value after all the entries in the window are sorted numerically. For an even number of entries, there is more than one possible median.

2.5 Weiner Filter

In signal processing, the Weiner filter is a filter used to produce an estimate of a desired or target random process by filtering another random process through the filter. The wiener filter minimizes the mean square error between the estimated random process and the desired process. A Weiner filter is not an adaptive filter because the theory behind this filter assumes that the inputs are stationary.

The goal of the Weiner filter is to filter out noise that has corrupted a signal. It based on a statistical approach. Typical filters are designed for a desired frequency response. The Weiner filter approaches filtering from a different angle. One is assumed to have knowledge of the spectral properties of the original signal and the noise, and one seeks the LTI filter whose output would come as close to the original signal as possible.

Weiner2 low pass-filters an intensity image that has been degraded by constant power additive noise. Weiner2 uses a pixel wise adaptive wiener method based on statistics estimated from a local neighbourhood of each pixel. J=weiner2 (I, [m n], noise) filters the image I using pixel wise adaptive Weiner filtering, using neighbourhoods of size m-by-n to estimate the local image mean and standard deviation. If you omit the [m n] argument, m and n default to 3. The additive noise (Gaussian white noise) power is assumed to be noise. [J, noise]=weiner2 (I,[m n]) also estimate the additive noise power before doing the filtering. Weiner2 returns this estimate in noise.

III. PROPOSED DENOISING ALGORITHM

Many recent image de noising techniques consist of two stages: first detecting the corrupted pixels and then estimating their original values. Traditional impulse detectors fail, when the impulses have few values, distributed in the entire range of grey-values. Noise is entered during image acquisition from its source and once entered it degrades the image and is difficult to remove. In order to achieve the noise cancellation in an image, non-linear filter works better than linear. This paper presents the joint scheme of Wavelet Transform using iterative noise density and Median Filtering to remove Salt and Pepper Noise in Digital Images. The first part of the paper derives the wavelet coefficients with slight increase in noise density and in second part these coefficients are further modified by median filter. The algorithm shows the remarkable improvement over Gaussian noise model and removes most of the noisy part from the image and maintains the visual quality. The level of wavelet decomposition is restricted to three. The renowned indexes Peak Signal to Noise Ratio (PSNR) and Root Mean Square Error (RMSE) demonstrate marked improvement of image de noising over Gaussian method.

3.1 Impulse Noise Model

The two common types of impulse noise are the Fixed Value Impulse Noise (FVIN) also known as Salt-and-Pepper Noise (SPN) and the Random-Valued Impulse Noise (RVIN) .They differ in the possible values which noisy pixels can take.

This model implies that the pixels are randomly corrupted by two fixed extreme values, 0 and 255 (for 8-bit grey-scale images), with the same probability. In the Fixed Range Impulse Noise (FRIN) model, instead of two fixed values, two fixed range at both ends with the length of m are assumed to be impulse noise values. Also the density of low intensity and high-intensity impulse noise might be unequal. The impulse probabilities don't have to be equal. The General Fixed-Valued Impulse Noise (GFN) or Multi-Valued Impulse Noise (MVIN).This models are included in the GFN model by choosing the appropriate set S as S1= {0,255} and S2= {0, 1, m – 1,255 – m+1,255 – m+2, 255}, respectively. The GFN can bridge the FVIN and the RVIN; if we choose s= [0 255] and all values have the same probability, the RVIN will be obtained.

3.2 Flow Chart

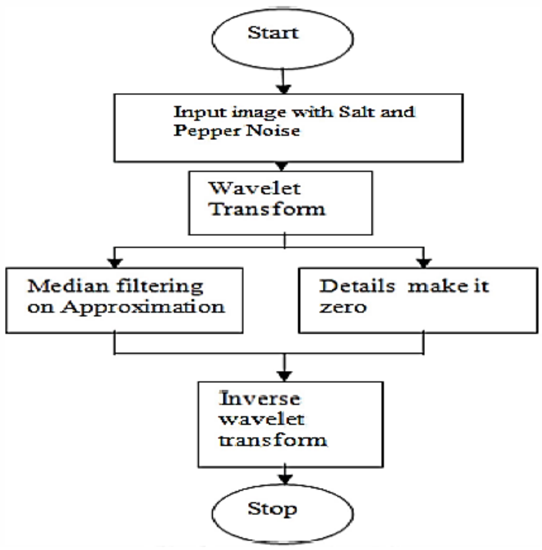


Fig.1: Flow Chart of the Proposed Method

3.3 Impulse Value Detector

The entropy of the image y is defined as follows:

$$\text{Entropy}(y) = \sum_{i=0}^{255} p_i \log p_i$$

where p_i is the probability of the grey-value i and can be interpreted as the normalized histogram of the image. In natural images, unlike the Gaussian noise, the impulse noise significantly decreases the image entropy.

The impulse value detector, iteratively, detects and removes the impulse grey-values. A grey-value is detected as an impulse if the corresponding pixels have the lowest correlation with their neighbors. After each iteration, by removing an impulse value, the image entropy increases. The process continues until the entropy becomes larger than the entropy threshold, thus it ensures that there are no more impulse values in the image. Images are often corrupted by impulse noise when they are recorded by noisy sensors or sent over noisy transmission channels. Many impulse noise removal techniques have been developed to suppress impulse noise while preserving image details. The median filter, the most popular kind of nonlinear filter, has been extensively used for the removal of impulse noise due to its simplicity. However, the median filter tends to blur fine details and lines in many cases. To avoid damage to good pixels, decision-based median filters realized by thresholding operations have been introduced in some recently In general, the decision-based filtering procedure consists of the following two steps: an impulse detector that classifies the input pixels as either noise-corrupted or noise-free, and a noise reduction filter that modifies only those pixels that are classified as noise-corrupted. In general, the main issue concerning the design of the decision-based median filter focuses on how to extract features from the local information and establish the decision rule, in such a way to distinguish noise-free pixels from contaminated ones as precisely as possible. In addition, to achieve high noise reduction with fine detail preservation, it is also crucial to apply the optimal threshold value to the local signal statistics. Usually a trade-off exists between noise reduction and detail preservation.

3.4 Discrete Wavelet Transform (DWT)

DWT is used to find the approximation and detailed coefficients of a discrete signal. DWT represents the time frequency analysis of discrete signal. Spectrum analysis and spectral behavior of the signal in time is essential and that is analyzed by DWT. In wavelet decomposition, signal breaks it into two classes; low pass and high pass. These classes are separately used to carry information of original signal as shown in Fig. 4.4.1.

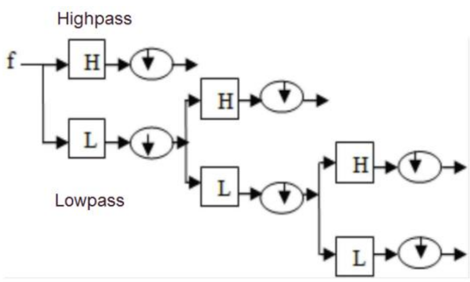


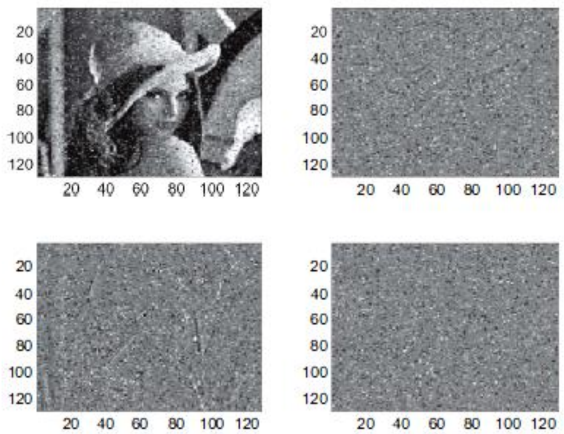
Fig 2: 2-D far Discrete Wavelet Transforms

3.5 Median Filter

Median filter (Non-linear filter) works on medial pixel value of its surrounding neighbors instead of mean filter (linear filter). To preserve the smoothness in a resultant image of median filter is most prominent choice. A median filter operates on pixel based noise reduction approach under structural constraints. In order to retain the smoothness and edges of median filters are best choice among the other nonlinear Filters. In the context of Order statistics theory, the intensity value of an image is critical choice in deciding the ranking of the neighboring pixels. To overcome the above criteria value of noisy pixel is replaced by the median value of surrounding Pixel values.

3.6. Proposed Wavelet Transform Median Filter

We present an integration of wavelet transform and median filter. This integrated approach is used for removal of salt and pepper noise from an image. Basically we are comparing the two most popular and elegant noise models, Gaussian model and proposed salt and pepper noise model. These two noise models are compared on the basis of iterative noise density in the proposed method. We exploit the powerful integration of wavelet transform and median filtering approach. These two schemes are jointly used to remove salt and pepper noise in an image. This combined approach overcomes the limitations of each of them. Multilevel wavelet decomposition is used in this paper. The multilevel wavelet decomposition is used to arrange coefficients in a manner that enables time-frequency analysis. These coefficients are improved via wavelet in order to achieve the smoothness. Smoothness is generally seen in the low pass region where as edges are seen in the high pass region. Further, low pass region has been improved in our method. We deploy Haar wavelet (Daubechies zero) decomposition at level three. Haar wavelet de composition is shown in the Fig.3 using Lena image. In our method wavelet decomposed an image into different offset up to three levels. These offsets are referred to as original and noisy images into HH3, HL3, LH3 and LL3 sub-bands, which are shown in Fig.4. We exploit an iterative noise density scheme in salt and pepper noise model. The filtering window is set of3x3 pixels. Of course 3x3 filtering window itself cannot be justified under restriction of the expansion of the filter size. Result needs the adaptation in a given filter according to optimum choice.



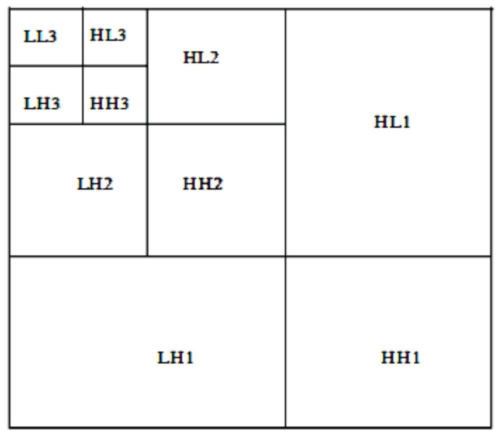


Fig.3: Wavelet decomposition of noisy Lena image   Fig.4: Wavelet Decomposition of image at three levels

To preserve smoothness and edges of an image we need wavelets operation in much more depth for which wavelet is reasonable choice. That is why an integration of wavelet base detorative noise density and Median filter is the best approach for salt and pepper noise instead of Gaussian noise. In this paper an image is corrupted by salt and pepper noise. That is why to estimate the noise densities of salt and pepper noise is essential and successfully measured in our algorithm, which is shown in Fig 4. First wavelet transform decomposed the noisy image Z (j, k) in the form of approximate and detail components.

In proposed method, the detail components are set to zero. Further the approximate part using the median filter. The following equations represent the proposed method.

$$Z(j,k) = D[j(j,k)] + I(j,k)$$

Where, J(j ,k) is original image, I(j ,k) is Noise signal, Z (j, k) is degraded image and D is degrading function.

I(j ,k) A == {l, ... E}X{l, ... F} is 256X256resize gray level image at pixel location (j, k)

Where {l, ...E } and {l, ... F } are the rows and columns of I (j, k) respectively. Z(j ,k) = {0,1}

Noisy image Z (j, k) probably identified in terms of noise intensities. For a good quality image needs the following noise intensities values 0 represents black (Pepper) and 1 represents white (Salt).

The DWT of degraded image Z (j, k) is W (j ,k) = W(j ,k)Z(j ,k)

This implies the approximation and details signals. Since image de noising schemes based on neighbour pixels. Original pixels of an image are caused by noise. In median approach, first identified those noisy pixels and comparing each of pixels by their neighbours. Noisy pixel secures some different value. Therefore this value is replaced by median value of its surrounding neighbour pixels. Apply median filtering upon the approximation coefficients of wavelet transform and estimate the noise variance.

Taking Inverse Discrete Wavelet Transform (IDWT); j(j ,k) = WT w(j ,k)

Our objective is to obtain the de noised image j (j, k) is close to original image j (j, k) as possible.

Error is e(j, k) = j(j, k) - j(j, k)

That is why Mean square error

$$MSE = \frac{1}{PQ}\sum_{p=0}^{P-1}\sum_{q=0}^{Q-1}[f(j,k)-\hat{f}(j,k)]^2$$

The Peak signal to noise ratio is given by

$$PSNR = 20\log_{10}\frac{255^2 PQ}{\sum_{p=0}^{P-1}\sum_{q=0}^{Q-1}[f(j,k)-\hat{f}(j,k)]^2}dB$$

IV. RESULTS & DISCUSSIONS

In this paper we used the software MATLAB 7.14.0 (R2012a).The proposed AIM filter was tested using natural images, i.e., Lena, peppers, camera man and lady. The performance of the proposed filter was tested for various levels of noise corruption and compared with the WTM filter. We generated noisy images by adding Salt-and-Pepper Noise (SPN). Though the proposed method highlights the different noise model for a standard Lena image is one of the major concerned of the work. It is observed that, as we slightly increase the noise density the smoothness of denoised image seems to be well preserved.

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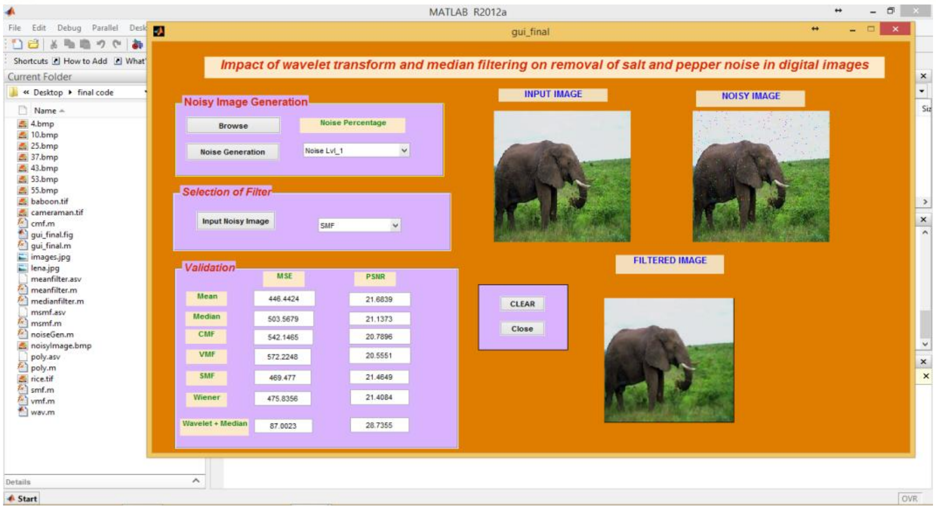
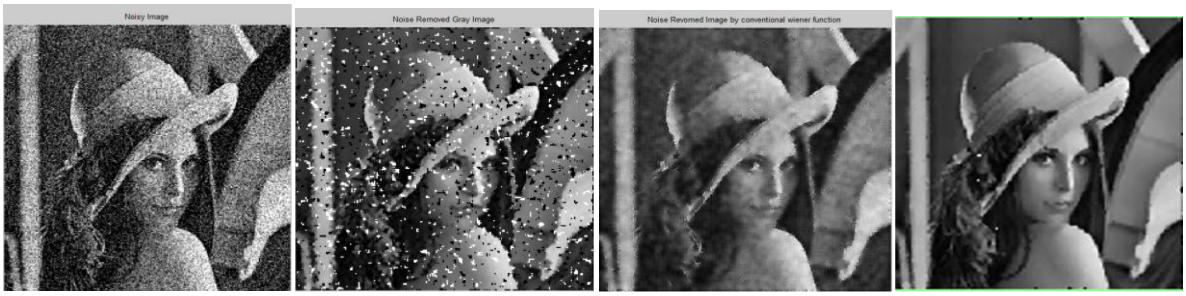


Fig.5: Simulation Result for Proposed Method

This method is also implemented for various images like Lena, Cameraman, Peppers and Lady.

a) Lena image b) cameraman image c) peppers image d) lady image

Fig.6:.Test images

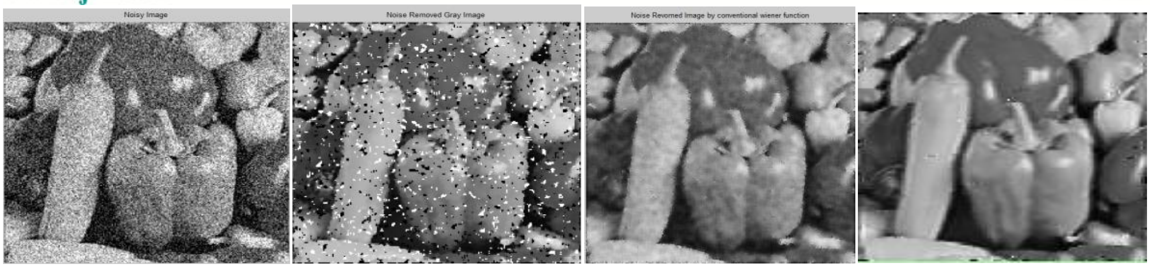


a) noisy image b) median filter c) weiner filter d)WTM filter

Fig.7: SPN Noise Removed by Using Various Filters in Lena Image

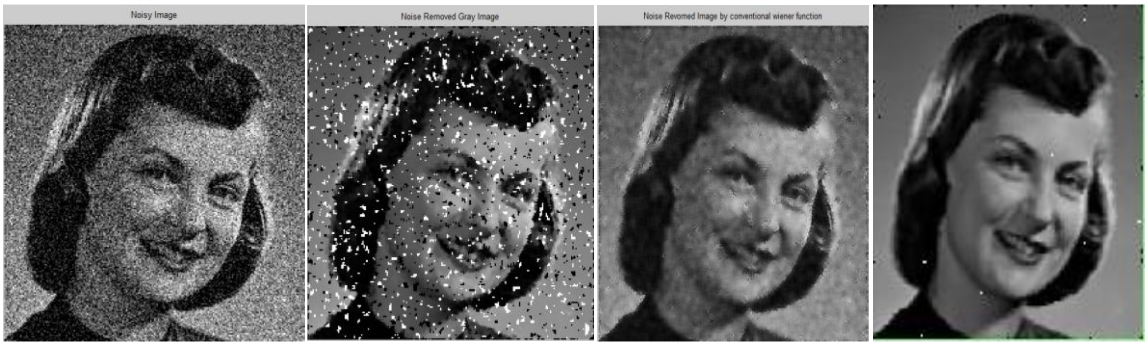
a) noisy image b) median filter c) wiener filter d)WTM filter

Fig.8:SPN Noise Removed by Using Various Filters in Cameraman Image



a) noisy image b) median filter c) wiener filter d) WTM filter

Fig.9: SPN Noise Removed by Using Various Filters in Peppers Image



a) noisy image b)median filter c)wiener filter d)WTM filter

Fig.10: SPN Noise Removed by Using Various Filters in Lady Image

Table.1: Comparision Values of Restored Lena Image

Parameters	Ideal values	Median filter	Wiener filter	WTM filter
Average absolute difference	0	0.083610	0.059120	0.021385
Signal to Noise ratio	High	7.423785	11.163218	19.492914
Peak Signal to Noise ratio	High	13.056723	18.481665	26.811301
Image fidelity	0	-0.132547	-0.076394	-0.011130
Mean Square Error	0	0.053978	0.013958	0.002050

Table 2: Comparison Values of Restored Cameraman Image

Parameters	Ideal values	Median filter	Wiener filter	WTM filter
Average absolute difference	0	0.104563	0.075547	0.028005
Signal to Noise ratio	High	8.543986	11.291354	18.854385
PSNR	High	12.678456	16.876545	24.439576
Image fidelity	0	-0.095310	-0.074201	-0.012947
Mean Square Error	0	0.050673	0.020528	0.003598

Table 3: Comparison Values of Restored Peppers Image

Parameters	Ideal values	Median filter	Wiener filter	WTM filter
Average absolute difference	0	0.132348	0.094597	0.031322
Signal to Noise ratio	High	5.452109	9.586384	19.069411
Peak Signal to Noise ratio	High	10.567451	14.752124	24.235150
Image fidelity	0	-0.123965	-0.109918	-0.012316
Mean Square Error	0	0.062310	0.029323	0.003303

Table 4: Comparison Values of Restored Lady Image

Parameters	Ideal values	Median filter	Wiener filter	WTM filter
Average absolute difference	0	0.087639	0.049911	0.018580
Signal to Noise ratio	High	8.342098	11.193334	19.059033
Peak Signal to Noise ratio	High	15.234165	18.123512	25.989211
Image fidelity	0	-0.094321	-0.075841	-0.012286
Mean Square Error	0	0.034001	0.011259	0.001840

The PSNR has been calculated for the images obtained after filtering with median, Weiner and WTM filters. The results are tabulated in the table. The obtained results show that:

1. Median filter's performance is low when compared with Weiner and WTM filter
2. Weiner filter performs well in low noise and its performance decreases with increases in noise density.

3. WTM filter performs well in high noise density; it gives better results, because of stronger correlation among adjacent pixels.

V. CONCLUSION

A more realistic model for the impulse noise called General Fixed-Valued Impulse Noise (GFN) also known as Salt-and-Pepper Noise (SPN) is introduced. This model implies that, instead of fixed values or ranges, impulses can take any subset of the entire grey-values dynamic range. This model requires a more complex impulse detector, because the noise values do not necessarily locate at the low and high intensities. A procedure for impulse value detection using the image entropy is proposed. For image restoration, wavelet transform median filter (WTM) is presented. In this filter, the noisy pixels which are farther than their nearest uncorrupted pixel, will be modified in more iterations. The WTM filter outperforms the best existing techniques for SPN removal. The proposed method is fast and quite suitable for real-time applications. By using AIM filter, we get clear and fast restoration of images when compared to the existing methods.

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