Removal of Random Valued Impulsive Noise

A thesis submitted in partial fulfillment

of the requirements for the degree of

Master of Technology

in

Computer Science and Engineering

by

Aloke Datta

Department of Computer Science and Engineering

National Institute of Technology Rourkela

Rourkela, Orissa, 769 008, India

May 2009

Removal of Random Valued Impulsive Noise

A thesis submitted in partial fulfillment

of the requirements for the degree of

Master of Technology

in

Computer Science and Engineering

by

Aloke Datta

under the guidance of

Banshidhar Majhi

Department of Computer Science and Engineering

National Institute of Technology Rourkela

Rourkela-769 008, Orissa, India

May 2008

Department of Computer Science & Engineering
National Institute of Technology Rourkela
Rourkela-769 008, Orissa, India.

Certificate

This is to certify that the work in the thesis entitled *Removal of Random Valued Impulsive Noise* submitted by *Aloke Datta* in partial fulfillment of the requirements for the award of the degree of Master of Technology in Computer Science and Engineering during the session 2007–2009 in the department of Computer Science and Engineering, National Institute of Technology Rourkela,is an authentic work carried out by him under my supervision and guidance.

To the best of my knowledge, the matter embodied in the thesis has not been submitted to any other University/Institute for the award of any Degree or academic award.

Prof. Bashidhar Majhi
Professor and HOD
Department of Computer Science & Engineering
National Institute of Technology
Rourkela-769008 Orissa (India)

Place: NIT Rourkela
Date: 26 May 2009

Acknowledgment

I would like to express my heartfelt thanks to my guide, Prof. Banshidhar Majhi, for his guidance, support, and encouragement during the course of my master study at the National Institute of Technology, Rourkela. I am especially indebted to him for teaching me both research and writing skills, which have been proven beneficial for my current research and future career. Without his endless efforts, knowledge, patience, and answers to my numerous questions, this research would have never been possible.The experimental methods and results presented in this thesis have been influenced by him in one way or the other. It has been a great honor and pleasure for me to do research under his supervision.

I am very much indebted to Prof. Pankaj Kumar Sa for his help and support, whenever I face problem during my work. Special thanks goes to Mr. Ratnakar Dash for his help.

I am also thankful to Prof. S. K. Rath, Prof. S. K. Jena,Prof. A. K. Turuk,Prof. B.D.Sahoo, Prof. D. P. Mohapatra, Prof. R. Baliarsingh, Prof. P. M. Khilar, Prof. S. Chinara, Prof. K. Sathya Babu for giving encouragement during my thesis work.

I thank all the members of the Department of Computer Science and Engineering, and the Institute, who helped me by providing the necessary resources, and in various other ways, in the completion of my work.

I thank my parents and all my family member for their unlimited support and strength. Without their dedication and dependability, I could not have pursued my MTech. degree at the National Institute of Technology Rourkela.

I thank to all my friends for being there whenever I needed them. Thank you very much everybody. I have enjoyed every moment with you.

I want to dedicate this thesis to my sister. In one word, I can say that she inspires me in every step of my life.

Aloke Datta

Abstract

In digital Image Processing, removal of noise is a highly demanded area of research. Impulsive noise is common in images which arise at the time of image acquisition and or transmission of images. Impulsive noise can be classified into two categories, namely Salt & Pepper Noise (SPN) and Random Valued Impulsive Noise (RVIN). Removal SPN is easier as compared to RVIN due to its characteristics. The present work concentrates on removal of RVIN from images.

Most of the nonlinear filters used in removal of impulsive noise work in two phases, i.e. detection followed by filtering only the corrupted pixels keeping uncorrupted ones intact. Performance of such filters is dependent on the performance of detection schemes. In this work, thrust has been put to devise an accurate detection scheme and a novel weighted median filtering mechanism.

The proposed detection scheme utilises double difference among the pixels in a test window. The difference is computed along four directions namely, horizontal, vertical, and two diagonals to capture the edge direction if any exists. This helps to identify, whether the test pixels under consideration is an edge pixel or a noisy one. Subsequently, the corrupted pixels are passed through in weighted median filter, where more weights are assigned to those pixels which lie in a minimum variance direction among all the four. Extensive simulation has been carried out at various noise conditions and with different standard images. Comparative analysis has been made with existing standard schemes with suitable parameters such as Peak Signal to Noise Ratio (PSNR), fault detection and misses. It has been observed in general that the proposed schemes outperforms its counterparts at low and medium noise conditions and performs at par at high noise conditions with low computational overhead. The low computational requirements have been substantiated with number of operations required for single window operation and overall time required for detection and filtering operation.

In addition, every detector utilizes a threshold value which is compared with a predefined computed value to decide whether the pixel under consideration is corrupted. Fixed threshold may perform well for one image at a particular noise condition. How-

ever, generalization is not possible for a fixed threshold. Hence, requirement for an adaptive threshold is realised. In the later part of this thesis, we propose an impulsive detection scheme using an adaptive threshold. The adaptive threshold is determined from an Artificial Neural Network (ANN) using various statistical parameters of noisy image like (μ, σ^2, μ_4) as inputs. The performance of this scheme is also compared with simulation results.

Contents

List of Figures

List of Tables

Chapter 1

Introduction

Impulsive Noise

Spatial Filter

Problem Statement

Performance Measures

Literature Review

Motivation

Thesis Organization

Chapter 1

Introduction

An image may be defined as a two dimensional function, f(x, y), where x and y are spatial coordinates, and the amplitude of f at any pair of coordinates (x, y) is called the intensity or gray level of the image at that point. When x, y and the amplitude values of f are all finite, discrete quantities, we call the image a digital image. The field of digital image processing refers to processing digital images by means of a digital computer. Image restoration is a fundamental step of digital image processing [1].

The entire process of image processing and analysis starting from the receiving of visual information to the giving out description of the scene, may be divided into three major stages which are also considered as major sub-areas, and are given below:

1. Discretization and representation: converting visual information into a discrete form; suitable for computer processing; approximating visual information to save storage space as well as time requirement in subsequent processing.

2. Processing: improving image quality by filtering etc.; compressing data to save storage and channel capacity during transmission.

3. Analysis: extracting image features; quantifying shapes, registration and recognition.

In the initial stage, the input is a scene (visual information), and the output is corresponding digital image. In the secondary stage, both the input and the output are images where the output is an improved version of the input. And, in the final stage, the input is still an image but the output is a description of the contents of that image [2]. A

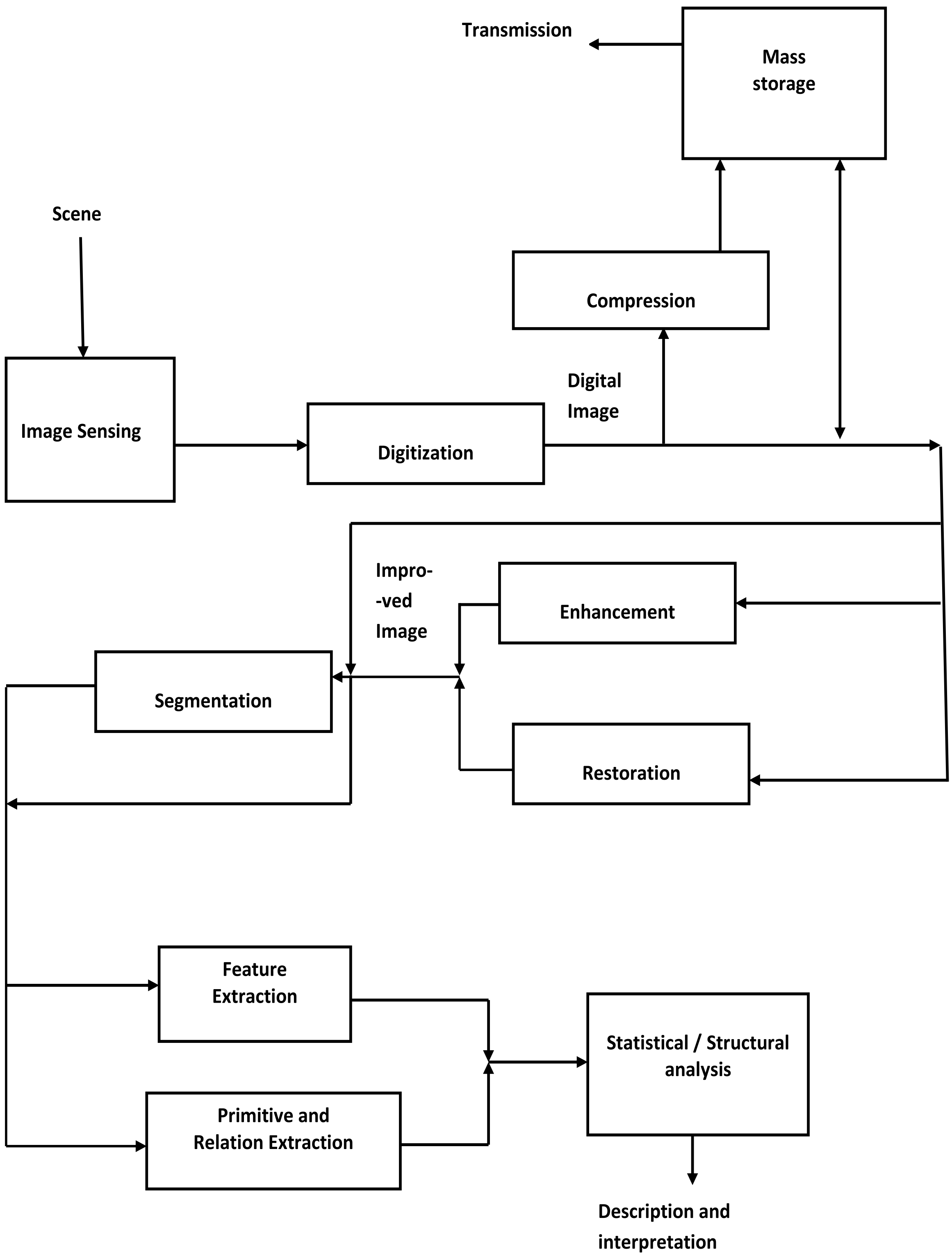


Figure 1.1: Different stages of image processing and analysis scheme

schematics diagram of different stages is shown in Figure 1.1. The figure is taken from the book specified in [2].

Out of the sub-branches of digital image processing, diagrammatically represented above, this thesis deals with image restoration. To be precise, the thesis devotes on a part of the image restoration i.e. noise removal from images. Accurately, it is about the denoising of one particular type of noise i.e. random valued impulsive noise, stated in the Problem Definition.

1.1 Image Restoration

Restoration attempts to reconstruct or recover an image that has been degraded by using a priori knowledge of the degradation phenomenon. Restoration techniques are primarily modelling of the degradation and applying the inverse process in order to recover the original image. The degradation function together with an additive noise operates on an input image f(x, y) to produce a degraded image g(x, y). Given g(x, y), some knowledge about the degradation function h(x, y) and some knowledge about the additive noise term $\eta(x, y)$, the objective of restoration is to obtain an estimate of the original image [1].

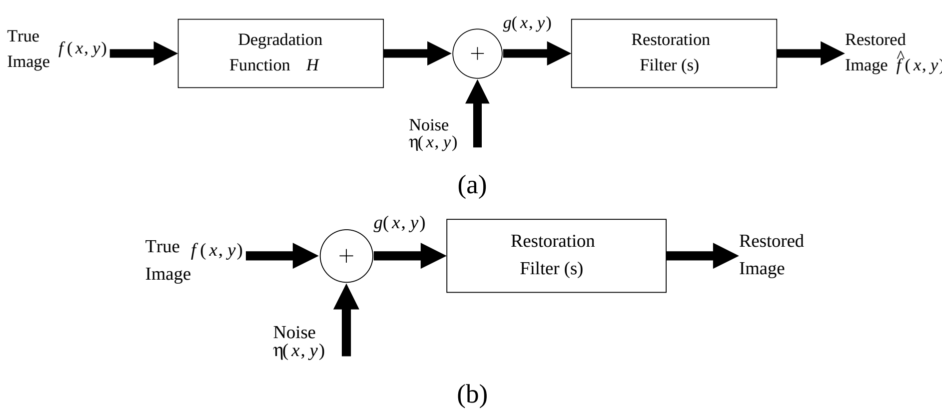


Figure 1.2: (a) Model of the image degradation/restoration process, (b) Model of the Noise Removal Process.

The degraded image is given in spatial domain by

$$g(x, y) = f(x, y) * h(x, y) + \eta(x, y) \tag{1.1}$$

In this thesis, it is assumed that the degradation function is the identity operator, and we deal only with degradations due to noise. So the degraded image is:

$$g(x,y) = f(x,y) + \eta(x,y) \tag{1.2}$$

1.2 Noise Model

Noise is a disturbance that affects a signal and that may distort the information carried by the signal. It can be Random variations of one or more characteristics of any entity such as voltage, current, or data. Otherwise it is a random signal of known statistical properties of amplitude, distribution, and spectral density. Loosely, noise can be defined as any disturbance tending to interfere with the normal operation of a device or system.

Image noise is a random, usually unwanted, variation in brightness or color information in an image. Image noise can originate in film grain, or in electronic noise in the input device (scanner or digital camera) sensor and circuitry, or in the unavoidable shot noise of an ideal photon detector.

Digital images are prone to a variety of types of noise. Noise is the result of errors in the image acquisition / transmission process that result in pixel values that do not reflect the true intensities of the real scene. There are several ways that noise can be introduced into an image, depending on how the image is created. For example: If the image is scanned from a photograph made on film, the film grain is a source of noise. Noise can also be the result of damage to the film, or be introduced by the scanner itself. If the image is acquired directly in a digital format, the mechanism for gathering the data (such as a CCD detector) can introduce noise. Electronic transmission of image data can introduce noise [2].

The spatial component of noise is based on the statistical behaviour of the intensity values. These may be considered as random variables, characterized by a probability density function (pdf). a probability density function (pdf), or density, of a random variable is a function which describes the density of probability at each point in the sample space. The probability of a random variable falling within a given set is given by the integral of its density over the set. Some commonly found noises are Gaussian noise, Rayleigh noise, Gamma noise, Exponential noise, Impulsive noise and so on..

1.3 Spatial Filtering

Spatial filtering is preferred when only additive noise is present. The different classes of filtering techniques exist in spatial domain filtering.

- Mean Filter
- Order-Statistics Filter
- Adaptive Filter

1.3.1 Mean Filter

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. There are various type of mean filter i.e. arithmetic mean filter, geometric mean filter, harmonic mean filter, contra harmonic mean filter. The arithmetic and geometric mean filters are well suited for random noise like Gaussian or uniform noise. The contra harmonic filter is well suited for impulsive noise [1].

1.3.2 Order-Statistics Filter

Order statistics (OS) are the characteristics of sorted data within a sliding window. The minimum, maximum and median are special cases of order statistics. Order statistics are extremely robust to outlier data and are used when outlier data is problematic. Order Statistics filters are non-linear and non-stationary (shift-variant). Order -statistics filters are spatial filters whose response is based on ordering (ranking) the pixels contained in the image area encompassed by the filter. The response of the filter at any point is determined by the ranking result. Median filter, Max and min filters, Midpoint filter, Alpha-trimmed mean filter are some of the order-statistics filter. Median filter replaces the value of a pixel by the median of the gray levels in the neighbourhood of that pixel. Pixel value is replaced by minimum and maximum gray levels of the window respectively for min and max filter. The midpoint filter simply computes the midpoint between the maximum and minimum values in the area encompassed by the filter. Median filters are particularly effective in the presence of impulse noise [1].

1.3.3 Adaptive Filter

Adaptive filters change its behavior based on the statistical characteristics of the image inside the filter window. Adaptive filter performance is usually superior to non-adaptive counterparts. But the improved performance is at the cost of added filter complexity. Mean and variance are two important statistical measures using which adaptive filters can be designed. For example if the local variance is high compared to the overall image variance, the filter should return a value close to the present value. Because high variance is usually associated with edges and edges should be preserved. Adaptive, local noise reduction filter and adaptive median filter are the example of adaptive filter [1].

1.4 Problem statement

Impulsive 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:

$$x(i,j) = \begin{cases} \eta(i,j) & \text{with probability } p \\ y(i,j) & \text{with probability } 1-p \end{cases} \tag{1.3}$$

Where $x(i,j)$ denotes a noisy image pixel, $y(i,j)$ denotes a noise free image pixel and $\eta(i,j)$ 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. $\eta_{i,j} \in [L_{min}, L_{max}]$ where L_{min} and 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.

The difference between SPN and RVIN may be best described by Figure 1.3. In the case of SPN the pixel substitute in the form of noise may be either $L_{min}(0)$ or $L_{max}(255)$. Where as in RVIN situation it may range from L_{min} to L_{max}. 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.

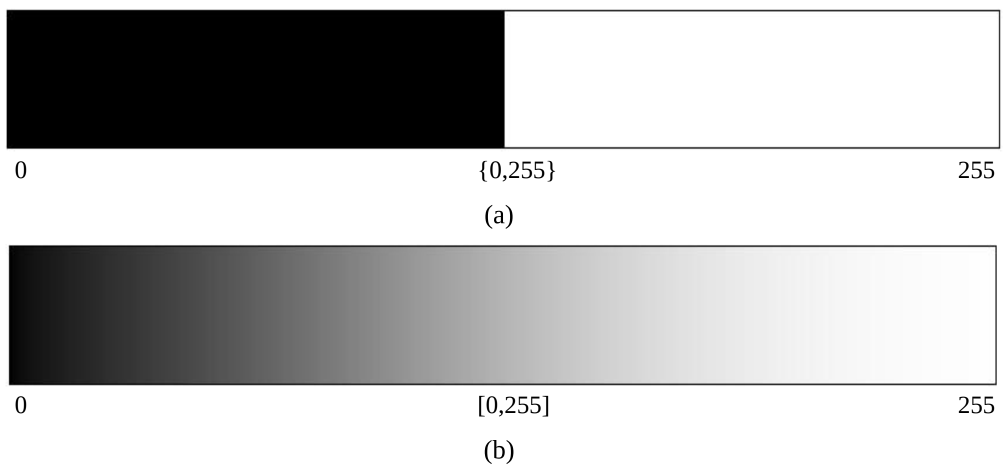


Figure 1.3: Representation of (a) *Salt & Pepper Noise* with $R_{i,j} \in \{n_{min}, n_{max}\}$, (b) *Random Valued Impulsive Noise* with $R_{i,j} \in [n_{min}, n_{max}]$

1.5 Performance Measures

The metric used for performance comparison of different filters are defined below.

a. **Mean Squared Error (MSE) and Peak Signal to Noise Ratio($PSNR$)**

In statistics, the mean squared error or MSE of an estimator is one 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.

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. The basic idea is to compute a single number that reflects the quality of the reconstructed image. Reconstructed images with higher PSNR are judged better [4].

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

$$PSNR(dB) = 10 \log_{10} \left(\frac{255^2}{\frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} \left(Y_{i,j} - \hat{Y}_{i,j} \right)^2} \right) \tag{1.4}$$

b **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.

1.6 Literature Review

The one of the emerging field of image processing is removal of noise from a contaminated image. Many researchers have suggested a large number of algorithms and compared their results. The main thrust on all such algorithms is to remove impulsive noise while preserving image details. Some schemes utilize detection of impulsive noise followed by filtering where as others filter all the pixels irrespective of corruption. In this section an attempt has been made for a literature review for the filtering of random-valued impulsive noise.

1.6.1 Random Valued Impulsive Noise Removal

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 is 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.

- ***Adaptive Center-Weighted Median Filter (ACWM) [5]***

  It devises a novel adaptive operator, which forms estimates based on the differences between the current pixel and the outputs of center-weighted median (CWM) [6] 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.

- ***Multi-State Median Filter (MSM) [7]***

  It 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.

- ***Tri-State Median Filter (TSM) [8]***

  It is 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.

- ***Advanced Impulse Detection Based on Pixel-Wise MAD (PWMAD) [9]***

  It is 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.

- ***Signal-Dependent Rank Order Mean (SDROM) Filter [10]***

  It is 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 multistate 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.

- ***Directional Weighted Median Filter (DWM) [11]***

Another method 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. First it considers a 5X5 window. Now it considers the four directions: horizontal, vertical and two diagonal. Each direction there is 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 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.

1.6.2 Simulation, Results and Discussions

Figure 1.5 shows the PSNR of DWM filter where iterations are varied from 1 to 10 for the Lena image which is corrupted by RVIN where noise probability are 10%, 30% and 50% respectively. From these graph it is concluded that DWMF gives the best result at iteration 8 to 10.

Lena image corrupted with RVIN (5% to 50% of noise) is subjected to the different filtering schemes discussed above and their performance is measured using measurement metrics. Table 1.1 lists the PSNR of some well known filter of RVIN. Figure 1.4 shows the graphical comparison of all the previous discussed filter .

Table 1.1: Comparative Results in PSNR (dB) of different filters for *Lena* image corrupted with RVIN of varying strengths

Method	5%	10%	15%	20%	25%	30%	40%	50%	60%
SD-ROM	39.22	35.89	34.09	32.48	31.05	29.86	27.32	24.96	22.35
ACWM	35.72	34.47	33.41	32.44	31.35	30.40	27.86	25.66	22.51
PWMAD	36.46	34.86	32.69	30.58	28.01	25.94	22.41	19.42	17.08
DWM	36.05	35.15	34.48	33.81	33.09	32.43	30.64	29.14	26.57

1.7 Motivation

From the problem statement it can be concluded that removal of SPN is easier rather than RVIN. Most of the reported schemes work well under the SPN but fails under RVIN, which is more realistic when it comes to real world applications. It is also observed the performance of any filtering scheme is dependent on the detection mechanism. The better is the detector; the superior is the filtering performance. Hence the performance of a detector plays a vital role. The detector performance is solely dependent on a threshold value which is compared with a pre computed numerical value. To improve the detector performance need for an adaptive threshold is an utmost necessity which can be automatically determined from the characteristics of an image and the noise present on it.

In summary, the thesis objective is as follows:

- To work towards improved and efficient detectors for identifying contaminated

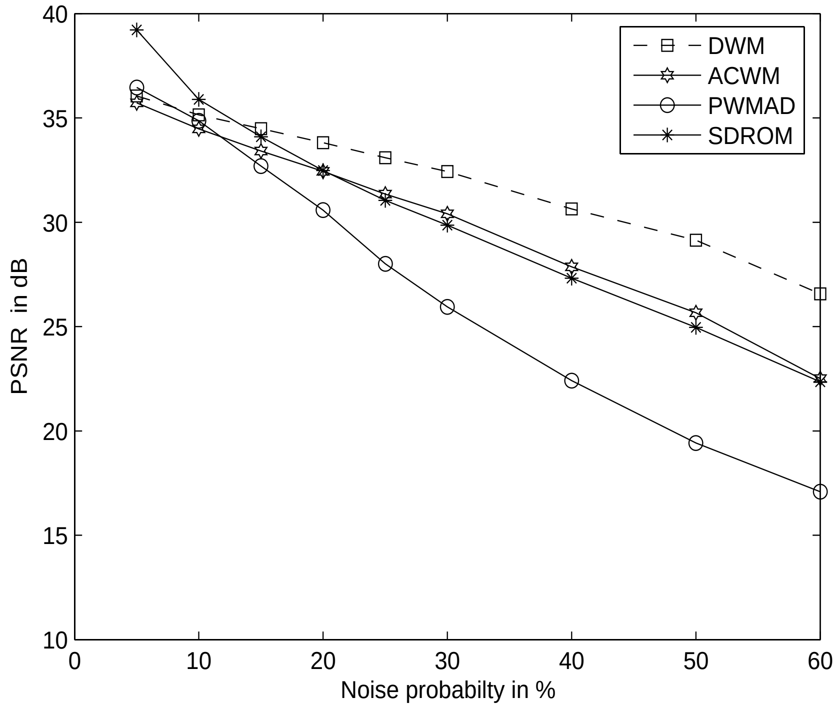


Figure 1.4: Comparison of PSNR(dB) variations of Different Schemes of Lena image corrupted with RVIN

pixels.

- To decrease the computational complexity of the filter.
- To devise adaptive thresholding techniques so that noise detection would be more reliable.

1.8 Thesis Organization

The rest of the thesis is organized as follows.

Chapter 2 proposes a new technique for denoising the random-valued impulsive noise. The proposed filter is based on double difference. In the detection phase, basically, we use the directionwise double difference to distinguish between a noise or a image details. Implementation and details comparison with previous filter has been made in chapter 2.

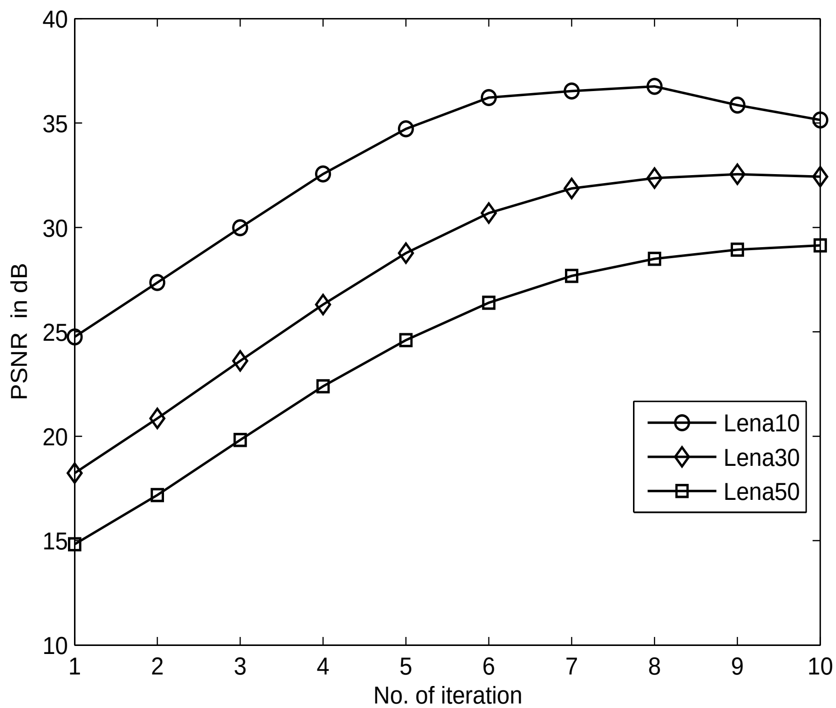


Figure 1.5: Number of Iteration vs PSNR(dB) of DWMF of Lena image corrupted with different noise probability

Chapter 3, focuses on adaptive threshold. An adaptive threshold value is used to determine the noise status of each pixel. Mean, Coefficient of Variance and Kurtosis are used to train the neural detectors. The approach uses Multilayer Perceptron network trained with back propagation algorithm to determine the adaptive threshold

Finally **Chapter 4** presents the concluding remark, with scope for further research work.

1.9 Summary

The fundamentals of digital image processing, sources of noise and brief discussion of noise, impulsive noise, type of impulsive noise- SPN and RVIN, the existing filtering schemes and their merits and demerits and the various image metrics are studied in this chapter. To derive the benefits of this paradigm, investigation has been made in this thesis to develop some novel schemes in the area of image denoising.

Chapter 2

IMPULSIVE NOISE REMOVAL SCHEME USING DOUBLE DIFFERENCE

Chapter 2

Impulsive Noise Removal Scheme Using Double Difference

The main challenge in impulse noise removal is to suppress the noise as well as to preserve the details (edges). 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; some of them are described in the previous chapter.

Here we suggest a new approach for removal of random-valued impulsive noise from images. The scheme works in two phases, namely a novel detection of contaminated pixels followed by the filtering of only those pixels keeping others intact. The detection scheme utilizes second order difference of pixels in a test window and the filtering scheme is a variation median filter based on the edge information.

2.1 Double Difference or Second Order Difference

The derivatives of a digital function are defined in term of differences. So here the term derivative or differences are used for same meaning. There are various ways to define these differences. However any definition uses for a first derivative

- must be zero in flat segments (areas of constant gray-level values)
- must be nonzero at the onset of a gray-level step or ramp and
- must be nonzero along ramps.

Similarly any definition of a second derivative

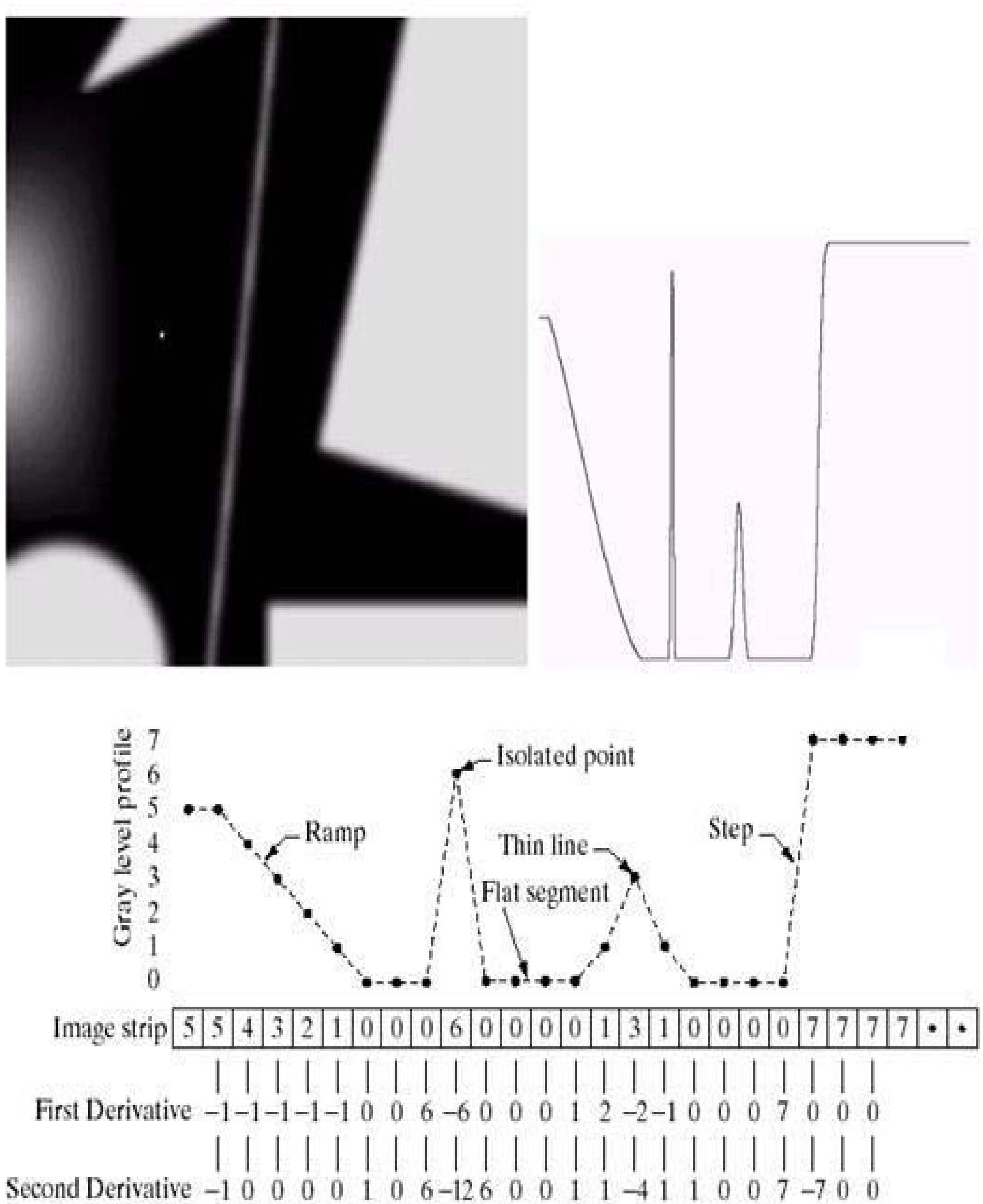


Figure 2.1: (a) A simple gray level image. (b) 1-D horizontal gray level profile along the center of the image and including the isolated noise point. (c) Simplified profile (the points are joined by dashed lines to simplify interpretation.

- must be zero in flat areas
- must be nonzero at the onset and end of gray-level step or ramp and
- must be zero along ramps of constant slope.

A basic definition of the first order difference of a one dimensional function $f(x)$ is the difference

$$\frac{\partial f}{\partial x} = f(x+1) - f(x) \tag{2.1}$$

Similarly, second-order difference may be defined as:

$$\frac{\partial^2 f}{\partial x^2} = f(x+1) + f(x-1) - 2f(x) \tag{2.2}$$

Figure 2.1 above describes the significance of first and second order difference for detecting flat region, detecting edges and discriminating noise from images. Comparing the response between first and second order derivatives, we arrive at the following conclusions. (1) First-order derivatives generally produce thicker edges in an image. (2) Second-order derivatives have stronger response to fine detail, such as thin lines and isolated points. (3) First order derivatives generally have a stronger response to gray level step. (4) Second order derivatives produce a double response at step changes in gray level. It is also noted for second-order derivatives that, for similar changes in gray-level values in an image, their response is stronger to a line than to a step and to a point than to a line.

This behaviour of second difference is exploited in the proposed schemes to determine the sanctity of a pixel. An impulse is nothing but change in gray level profile of an image. The second difference of an impulse will result in a spike. Also there will be a spike for an edge. In order to differentiate between these two spikes a second order difference based impulse detection mechanism is employed at location of the test pixel. Once a test pixel is identified as an impulse it is immediately filtered by replacing it with the weighted median of the surrounding pixels. This filtered pixel also takes part in the noise detection phase of the next test pixel and subsequent filtering, if needed [1].

2.2 Proposed Impulse Detector

The proposed detection algorithm is based on the second order difference (SOD) among pixels in a test window to determine the noise status of the centre pixel. The SODs have a stronger response to fine details, such as thin lines and isolated points. For an isolated noise point, the SOD yields a value of larger magnitude. This property has been exploited in the proposed impulse detctor.

Consider a 3×3 window W symmetrically surrounding the test pixel $x(i,j)$ as

$$W = \{x(i+s, j+t)| -1 \leq s, t \leq 1\} \tag{2.3}$$

Edges aligned with four main directions are captured by computing the SODs as in (2.4).

$$d_k = |x(i+u, j+v) + x(i-u, j-v) - 2x(i,j)| \tag{2.4}$$

where, $(k, u, v) = \{(1,1,1), (2,0,1), (3,-1,1), (4,-1,0)\}$

Then, the minimum of these four second-order-differences are used for impulse detection, which can be denoted as

$$\mathrm{d} = \min \{d_k : 1 \leq k \leq 4\} \tag{2.5}$$

Depending on the value of d, the following three decisions are made—

1. when the value of d is small, the test pixel is a noise-free flat region pixel as all the four direction differences are small.

2. a test pixel when falls on an edge shall yield smallest SOD along the edge resulting in a smaller value of d. Hence, the test pixel is noise-free.

3. a large value of d implies that the test pixel is noisy as it has all large SODs.

The above analysis infers that the impulse can be identified by applying a hard limiting operation on d by suitably choosing a threshold T.

2.3 Proposed Filter

Once the coordinate of an impulse is located the noisy pixel is replaced with an appropriate intensity value. This substitution is computed using a weighted median filter supported with four directional information. Let $S_k(i, j)$ denotes the gray level difference between the two neighbouring pixels of $x(i, j)$ in the k^{th} direction $(1 \leq k \leq 4)$.

$$S_k(i, j) = |x(i + u, j + v) - x(i - u, j - v)| \tag{2.6}$$

$$\text{where, } (k, u, v) = \{(1, 1, 1), (2, 0, 1), (3, -1, 1), (4, -1, 0)\}$$

These four values of S_k signifies the closeness of the neighbouring pixels. Let D_k be the direction of minimum $S_k,\ (1 \leq k \leq 4)$. This shows that the pixels aligned along D_k are closest to each other and the center value should be close to them. Thus, these pixels are assigned with extra weight (w) while restoring the noisy pixels. If the test pixel $x(i, j)$ is found to be noisy, it is replaced with $r(i, j)$ that can be expressed as

$$r(i, j) = \text{median}\{W,\ w\Diamond x_{D_k}\} \tag{2.7}$$

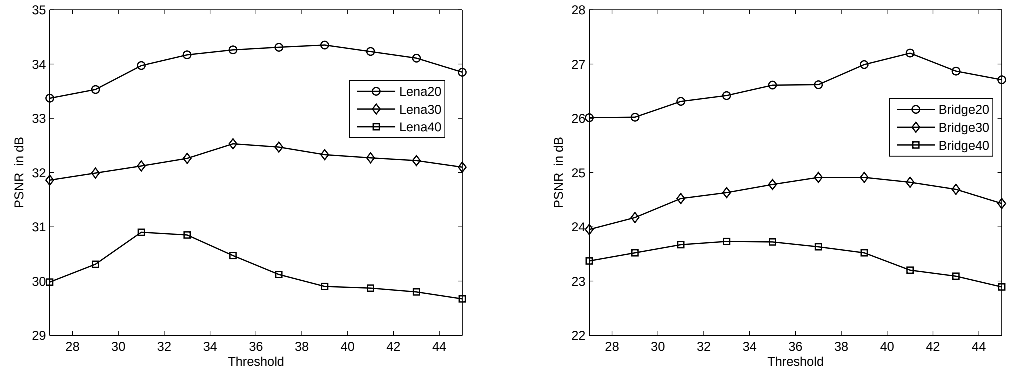
where, W is the window surrounding the test pixel as defined in (2.3), and x_{D_k} denotes the two neighbouring pixels of $x(i, j)$ along the direction D_k. The symbol $\Diamond$ is used as the repetition operator. This filtered pixel takes part in the noise detection process of subsequent windows making it a recursive process.

High accuracy of the proposed filter is ensured by recursively and iteratively applying the proposed scheme. Subsequent iterations use smaller threshold T as compared to the previous iterations in order to capture more noise. It has been observed from the simulations conducted on a variety of standard images that the following set of threshold values yields satisfactory results.

$$[T_1\ \ T_2\ \ T_3] = [35\ \ 25\ \ 18] \tag{2.8}$$

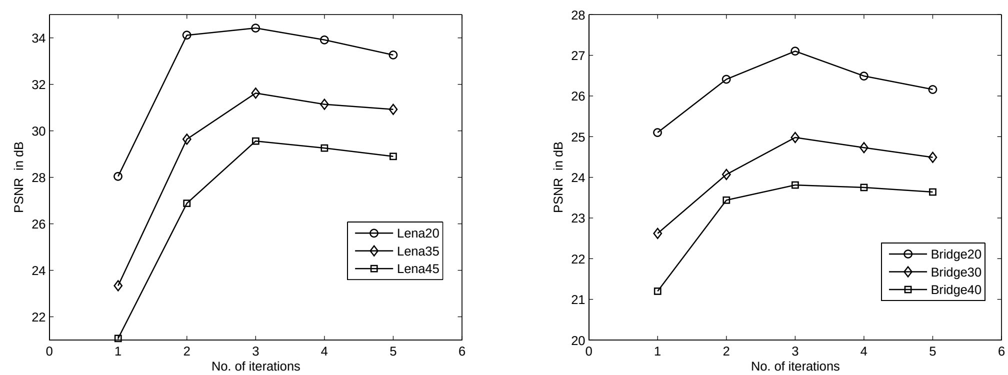
2.4 Simulation Results and Discussions

For the proposed scheme, it is decided it performs well for 3 iterations. The experimental results shown in the Figure 2.3 support the schemes also.Next, the first threshold



(a) (b)

Figure 2.2: Graphical Representation of PSNR(dB) value for Proposed scheme at Different Threshold value for 20%,30% and 40% corrupted image respestively for (a) Lena image, (b) Bridge image,



(a) (b)

Figure 2.3: Graphical Representation of PSNR(dB) value for Proposed scheme at Different number of Iterations for (a) Lena image, (b) Bridge image,

value is taken as 35. The Figure 2.2 shows the graph between PSNR value with respect to different Threshold value. From the observations it is concluded that threshold value is not fixed for all noise probability. But for taking a fixed threshold value it is better to take the average threshold which is 35.

To validate the proposed scheme, simulation has been carried out on standard images like *Lena*, *Boat*, and *Bridge* etc. The existing schemes are also simulated with the same set of images in the same environment. Both objective as well as subjective studies are performed by accumulating the results obtained from various schemes. The performance measures in terms of PSNR (dB) for *Lena* and *Bridge* images are shown in

Table 2.1 and Table 2.2 respectively. Table 2.3 lists the comparative performance analysis in terms number of false detections and miss detection among various schemes.

It may be observed from Table 2.1 and 2.2 that the proposed filter outperforms its counterparts except the recently reported scheme DWM filter which shows a slightly superior performance as compared to the proposed scheme beyond 40% noise densities.

To measure the subjective performance, the restored images by various filtering schemes are shown in Figure 2.4and 2.5 at 30% noise density. A closer look at the feathers and iris of the enlarged Lena image (Figure 2.5) justifies that the proposed scheme is good at detail preservation. The graphical representation of proposed filter and some existing scheme are shown in Figure 2.6.

Table 2.1: Comparison of PSNR (dB) for *Lena* Image

Method	10%	20%	30%	40%	50%	60%
SD-ROM	35.89	32.48	29.86	27.32	24.96	22.35
ACWM	34.47	32.44	30.40	27.86	25.66	22.51
PWMAD	34.86	30.58	25.94	22.41	19.42	17.08
DWM	35.15	33.81	32.43	30.64	29.14	26.57
Proposed	36.89	34.35	32.53	30.90	28.22	24.84

Table 2.2: Comparison of PSNR (dB) for *Bridge* Image

Method	10%	20%	30%	40%	50%	60%
SD-ROM	26.62	26.35	24.89	23.03	21.18	19.21
ACWM	25.89	25.14	23.99	22.61	20.88	19.09
PWMAD	25.98	25.22	22.91	20.27	17.86	15.77
DWM	26.02	26.50	24.87	24.09	23.08	21.41
Proposed	27.80	27.20	24.91	23.73	22.14	20.02

Table 2.3: Comparison of Miss and False Hit for *Lena* Image at Various Noise Conditions

Method	20%		30%		40%		50%	
	miss	false	miss	false	miss	false		
SD-ROM	8815	557	15223	625	32535	1115	32535	1115
ACWM	4140	15684	6533	16021	13370	17900	13370	17900
PWMAD	6061	17616	13816	13992	44320	9143	44320	9143
DWM	5545	7570	8611	7366	11738	7435	15445	7488
Proposed	4947	6118	7741	8523	10746	12021	14087	16187


(a)


(b)


(c)


(d)


(e)


(f)


(g)

Figure 2.4: Restored results of *Bridge* image corrupted with 30% of RVIN (a) True image, (b) Noisy image, (c) ACWMF, (d) PWMAD, (e) SDROM, (f) DWMF, (g) Proposed.

2.4.1 Comparison of DWM and Propose filter

By observing Table 2.1, we can conclude that our proposed filter provides the better result in PSNR for all other filter except DWM filter. DWM filter only gives the better result in PSNR value when the noise is near about or greater than 40%. Proposed filter give the better result than DWM filter up to 40% of noise. One thing we have to consider that we have to perform 10 iterations to get the better result in DWM filter, where as Proposed filter only needs 3 iterations. To save the time of approximately 7 iterations

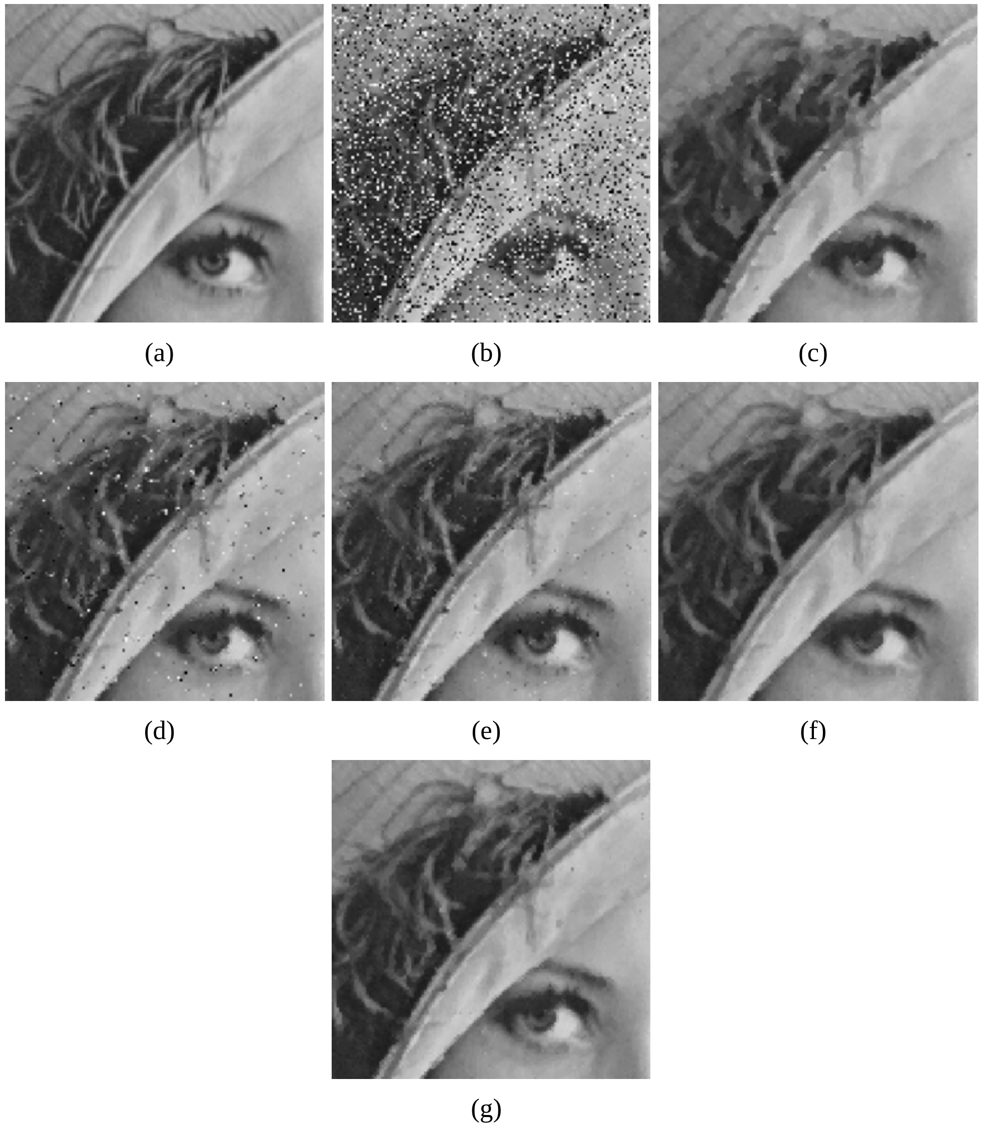


Figure 2.5: Restored results of enlarged *Lena* image corrupted with 30% of RVIN (a) True image, (b) Noisy image, (c) ACWMF, (d) PWMAD, (e) SDROM, (f) DWMF, (g) Proposed.

by compromising little bit with PSNR value is not negligible. Table 2.4 compares the result of Proposed filter to DWM filter in details.

In order to compare the result subjectively, we give some restored images in Figure 2.4 & Figure 2.5. There are a lot of noise patches in the images restored by the others, but by the Proposed & DWM filter, noticeable noises are too little. It is easy to see that excellent restoration results are obtained first by DWM filter and then by Proposed filter. Both of them can remove most noise while preserving details very well, even thin lines.

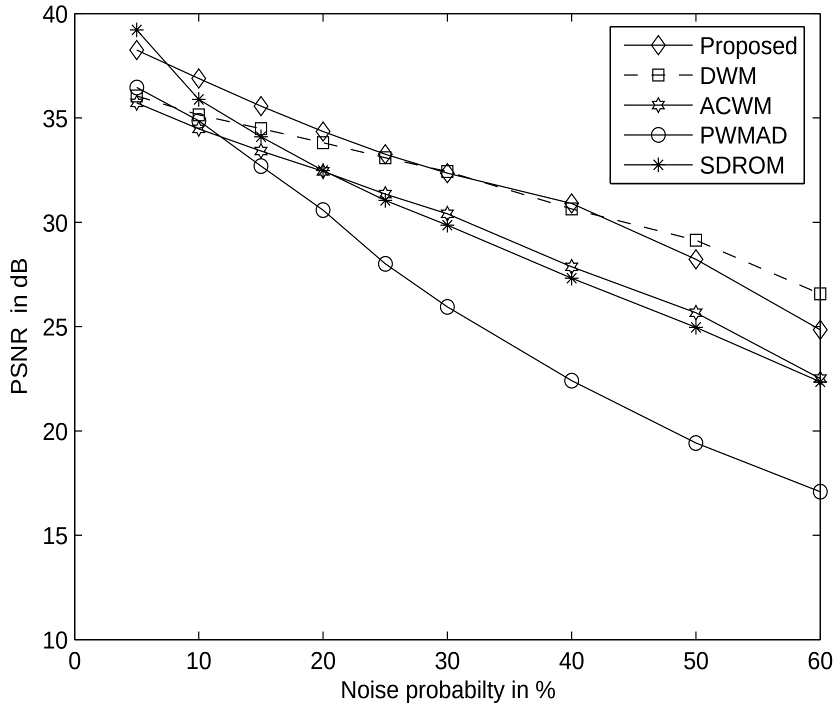


Figure 2.6: Graphical comparison of Some RVIN filters with Proposed Filter

Number of computations needed per single window detection as well as filtering between the proposed and DWM filter are shown in Table 2.5. This clearly reveals that there exists a remarkable difference in computational overhead.

Here we try to compare the time complexity of DWM filter and proposed filter. In DWM filter we consider a 5X5 window size. There are four directions and calculate the weighted differences in those four directions. In each, direction there are 5 pixel points, so there need four subtractions and then each differences are multiplied by a predefined weight according to the distance of the middle point (i.e. 1 or 2), so there are at least 2 multiplications. Then there are addition of these four numbers, i.e. there are 3 additions. To calculate each weighted difference in one direction, it needs 4 subtractions, 3 additions and 2 multiplications. Then for four directions, there are 16 subtractions, 12 additions and 8 multiplications are needed.

But for proposed filter, we consider 3X3 window size. We also consider the four directions, but in each direction there are only 3 points. Then we use second order difference in each direction. So, we need 1 addition, 1 subtraction and 1 multiplication for each direction. Overall we need 4 additions, 4 subtractions and 4 multiplications for all of the four directions.

Next the time taken by the remaining portion of the Propose filter and DWM filter are more or less same, except at one stage. Whenever it is needed to calculate the standard deviation in each direction, DWM filter has to calculate for 4 points whereas Propose filter has to do it for 2 points. So by the above discussion we just say that for each pixel point and for each iteration, DWM needs 12 subtractions, 8 additions and 4 multiplications more than proposed filter. One more thing is also that DWM filter has to repeat the same procedure 8 to 10 time for getting best output, where as proposed filter needs only 3 iterations.

From the simulation result we can say that proposed filter gives the better PSNR value than DWM filter when noise is less than 40% and whenever the noise is equal to or greater than 40% the DWM gives the better result only. Figure 2.7 shows the graphical comparison between DWM filter and Proposed filter. Table 2.6 shows the comparison of time taken to execute by proposed filter and DWM filter. This is verified by simulating the schemes in Matlab 7.0, Microsoft Windows XP (SP2) Operating System and Intel Pentium(R) 4 CPU 3.00 GHz with 1.99 GB of RAM

Table 2.4: Comparison of PSNR & noise detection results of Proposed & DWM filter for *Lena* Image at Various Noise Conditions

Noise in %	Proposed Filter			DWM Filter		
	PSNR	Miss	Fault	PSNR	Miss	fault
5	38.25	1180	4404	36.05	1334	7951
10	36.89	2397	4726	35.15	2677	7827
15	35.56	3709	5356	34.48	4172	7608
20	34.35	4947	6118	33.81	5545	7570
25	33.26	6358	7113	33.09	6957	7421
30	32.35	7741	8523	32.43	8611	7366
40	30.90	10746	12021	30.64	11738	7435
50	28.22	14087	16187	29.14	15445	7488
60	24.84	18252	20652	26.57	19506	8310

Table 2.5: Computational Overhead Between the Proposed and the DWM filter

Filter	Impulse Detection Phase			Filtering Phase		
	Window	Additions	Multiplications	Additions	Multiplications	Exponentiation
DWM	5×5	28	08	48	07	One square root
Proposed	3×3	08	04	42	01	00

Table 2.6: Time comparison of *Proposed* and *DWM* filter

Noise in %	Time taken by *DDM* filter	Time taken by *DDM* filter
5	8.70	34.93
10	10.11	38.26
15	11.60	42.37
20	13.10	45.45
25	14.51	49.37
30	16.15	53.39
40	19.45	60.59
50	23.31	68.93
60	27.03	78.75

2.5 Summary

This chapter proposes a new scheme to removal the RVIN from images. The proposed filter is an Impulsive noise removal scheme using double difference based detection and weighted median filter. In the detection phase, we introduce the direction wise double difference concept to detect a random-valued impulsive noise; basically it can distinguish a noise and an edge point nicely. Then contaminated pixel point is replaced by weighted median filter. Implementation of this scheme and comparison of result with previous scheme has been made thoroughly.

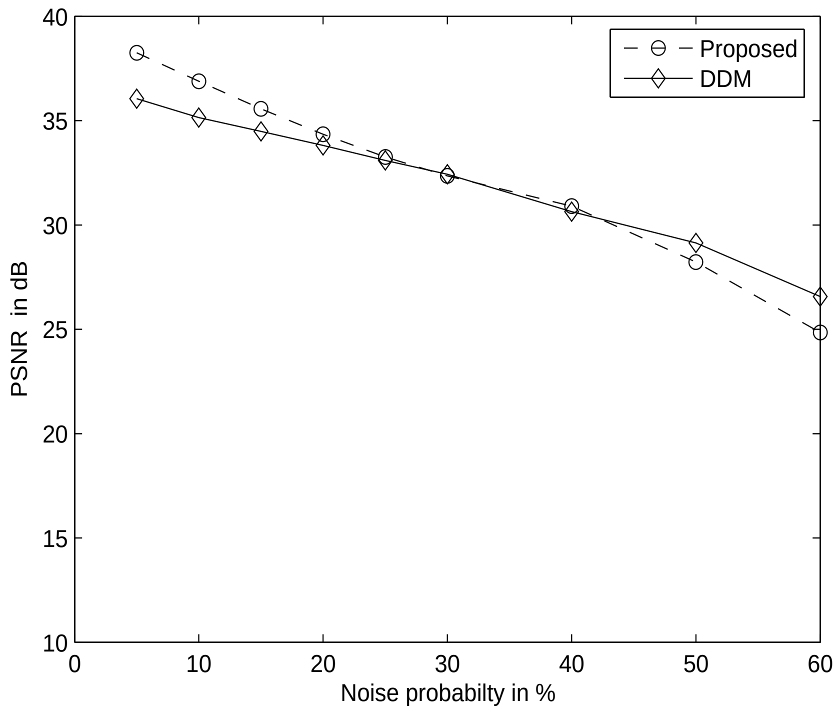


Figure 2.7: Graphical comparison of DWM & Proposed filter

Chapter 3

Adaptive Threshold

Chapter 3

Adaptive Threshold

Threshold plays a important role in performance of a filter. If a predefined parameter of a test pixel exceeds the threshold value, it is termed as contaminated. Although, the denoising techniques from images depends very much on the type of image characteristics and density of noise, but there cannot be one threshold value, which is applicable to all situation. A constant threshold value may not provide satisfactory performance for all circumstances.

From the following experiment, it is observed that a single threshold value does not serve the purpose as well as in different noise conditions. The steps are described as follows:

a. An image (say *Lena*) is corrupted with impulsive noise of densities 5%, 10%, 15%, 20%, 25%, 30%, 40% and 50%.

b. The first noisy image $Lena_5$ (the subscript is for 5% of noise) is subjected to the proposed algorithm outlined in Chapter 2 by varying the threshold value Θ between 0 and 1

c. Corresponding to each Θ one mean squared error (MSE) is obtained. The minimum among those MSEs is recorded asMSE_{min}.Also the corresponding threshold value is recorded as optimal threshold value Θ_{opt}. Figure 3.1 shows that the image achieves minimum MSE for 20% noise, denoted as MSE_{min}^{20} at $\Theta = 0.2118$ and let this threshold be denoted as Θ_{opt}^{20}.

d. Steps (b) and (c) are repeated for other noisy Lena, i.e. $Lena_i$,$i \in \{5\ 10\ 15\ 25\ 30\ 40\ 50\}$.

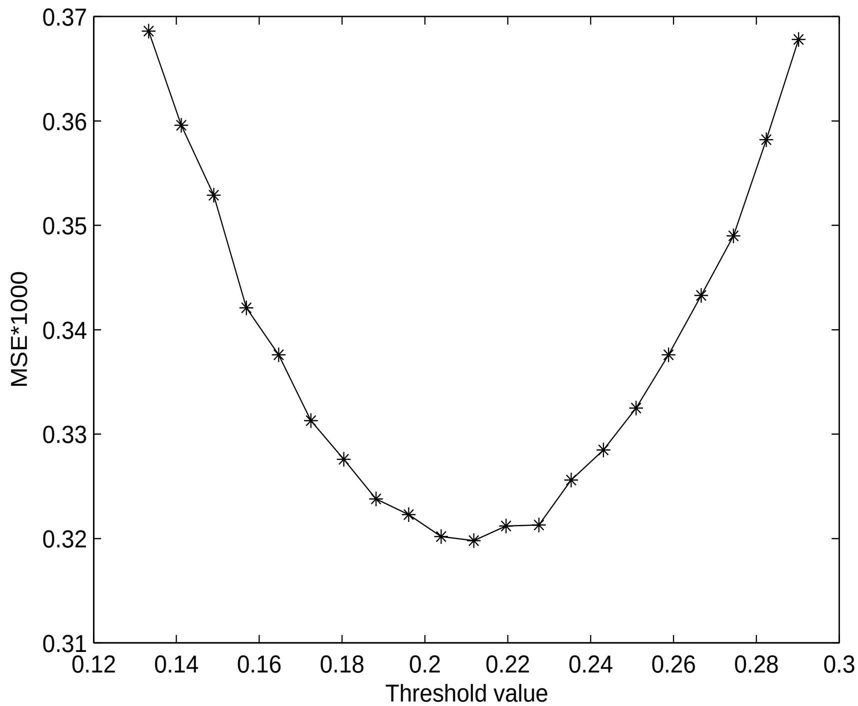


Figure 3.1: Variation of MSE at different threshold values for 20% RVIN for Lena image

e. The relationship between optimum thresholds versus the noise densities is shown in Figure 3.2. This clearly reveals that threshold needs to be different at different noise densities to minimize the error and hence to maximize the PSNR in restored images.

f. The overall relationship between MSE and its corresponding optimum threshold for different noise conditions for Lena image is shown in Figure 3.3. The Figure 3.4and Figure 3.5 also shows the same diagram for Boat and Bridge image.

It is, in general, observed that there exists an optimum threshold for every image and for a particular noise density. Even these values differ from image to image for the same noise density. In addition, the plot reveals clearly that there exists nonlinear relationship between optimum threshold and noise density as well as MSE.This is true for all other images. In a practical situation, the use of MSE or noise ratio to predict the threshold is ruled out as they need knowledge of the original image for computation. However, to alleviate this problem analysis have been made as follows. The minimum

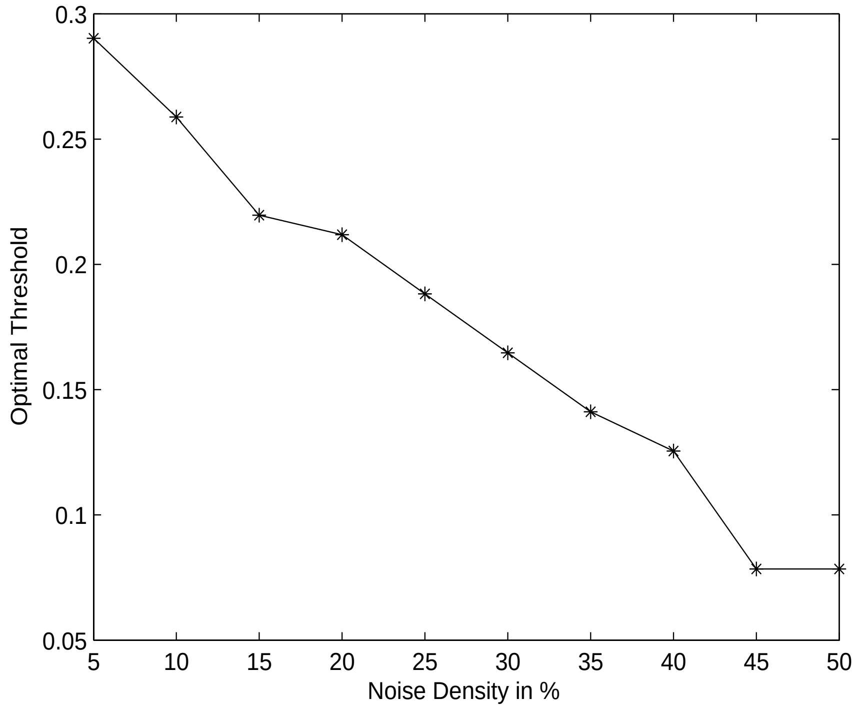


Figure 3.2: Variation of Optimal threshold at different noise percentage for Lena image.

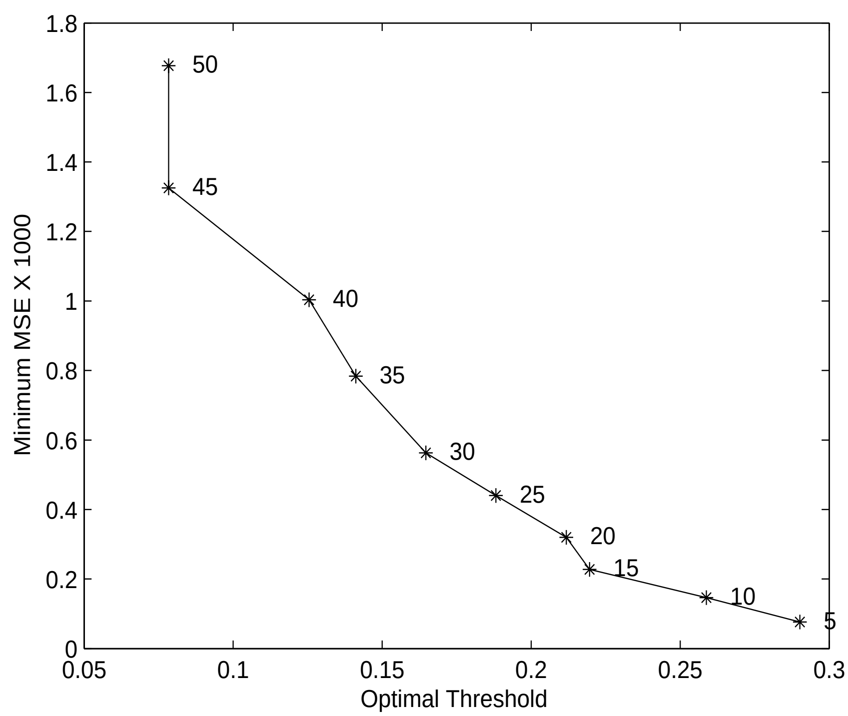


Figure 3.3: Variation of Minimum MSE at different Threshold values for Lena image

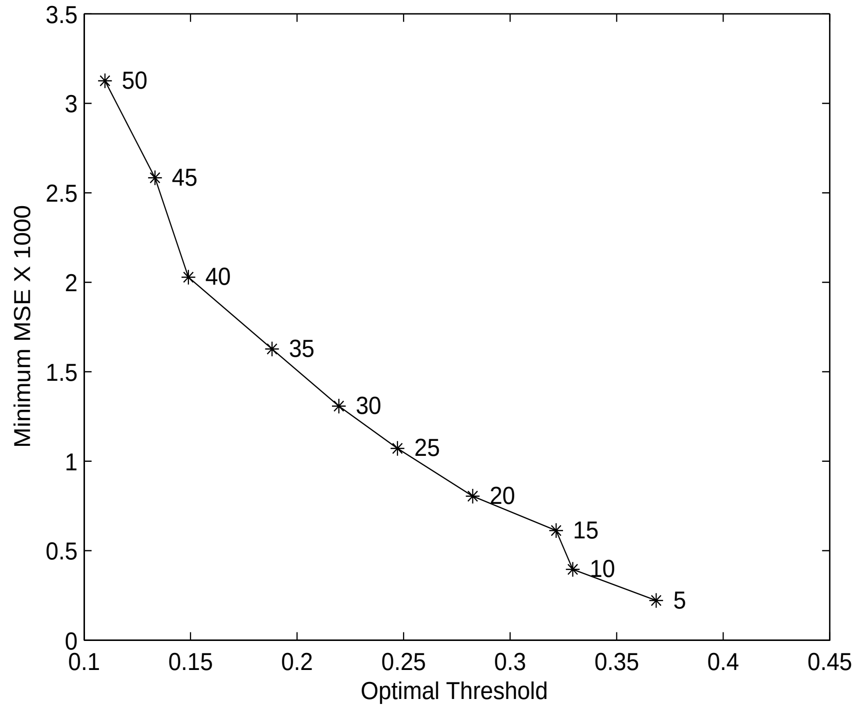


Figure 3.4: Variation of Minimum MSE at different Threshold values for Boat image

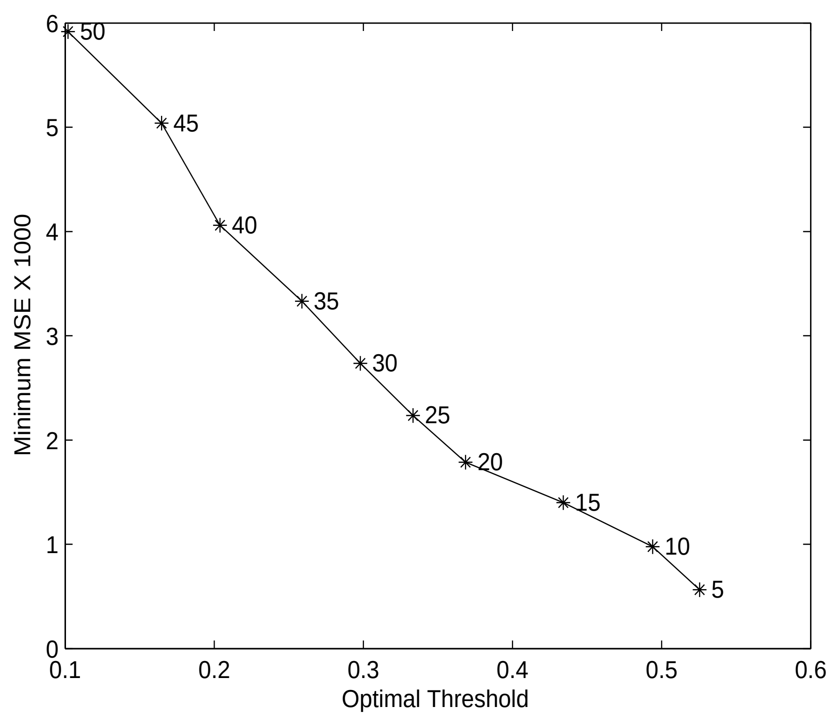


Figure 3.5: Variation of Minimum MSE at different Threshold values for Bridge image

MSE is inversely proportional to optimal threshold value,i.e.

$$MSE_{min} \propto \frac{1}{\Theta_{opt}} \tag{3.1}$$

also the noise percentage is inversely proportional to optimal threshold value, given as:

$$\eta \propto \frac{1}{\Theta_{opt}} \tag{3.2}$$

where, η is the noise percentage. Also it is known that:

$$\eta \propto \sigma^2 \tag{3.3}$$

and

$$\eta \propto \mu \tag{3.4}$$

Where, μ and σ^2 are the mean and variance of the noisy image respectively.

The experimental results give a direction that if an optimum threshold can be derived adaptively from a given noisy image, the noise detection becomes efficient. Here in Table.3.1 compare the result of proposed filter, discussed in chapter 2, which applies on contaminated Lena image one with Adaptive Threshold at different noise and another is fixed threshold value.

In practical image processing applications, parameters like noise percentage or MSE will not be helpful to predict the threshold because both need the knowledge of original image which is not available. Hence, parameter which can be derived from the given noisy image will be of great help to handle real life situations. For the purpose , statistical parameters like Coefficient of Variance and 4^{th} order Moment (Kurtosis) for noisy image is used to determine the adaptive threshold.

Statistical parameter called Coefficient of Variance for a noisy image is defined as :

$$CV \propto \frac{\sigma}{\mu} \tag{3.5}$$

Where,σ and μ are the standard deviation and mean of the noisy image respectively. To further extend the CVs for all noisy image of Lena are computed i.e. $CV^i \in$

$\{5, 10, 15, 20, 25, 30, 35, 40, 45, 50\}$. The relation between CVs and the optimal threshold is shown in Figure 3.6. This figure also gives the additional information regarding the existence of a non linear relationship between these two parameter.

Table 3.1: Details Comparison of *Proposed Filter* with Fixed threshold and variable Threshold applied on *Lena* image

Noise in %	Fixed Threshold				Variable Threshold			
	Threshold	PSNR	Miss	Fault	Threshold	PSNR	Miss	fault
5	35	38.25	1180	4404	74	41.16	2177	351
10	35	36.89	2397	4726	66	38.34	4069	694
15	35	35.56	3709	5356	56	36.42	5508	1595
20	35	34.35	4947	6118	54	34.96	7218	2136
25	35	33.26	6358	7113	48	33.56	8284	3606
30	35	32.35	7741	8523	42	32.50	9102	6169
40	35	30.90	10746	12021	32	30.98	9860	13928
50	35	28.22	14087	16187	20	28.76	8188	29831
60	35	24.84	18252	20652	11	25.12	6092	47893

Statistical parameter called 4_{th} order Moment or Kurtosis for a noisy image is defined as :

$$\mu_4 = \frac{1}{N} \sum_{i,j} (x(i,j) - \mu)^4 \tag{3.6}$$

Where $x(i,j)$ is the noisy image, μ is the mean of the image,$N = iXj$ is the size of the image. To further extend the Kurtosis for all noisy image of Lena are computed i.e. ${}_4^{(i)} \in \{5, 10, 15, 20, 25, 30, 35, 40, 45, 50\}$. The relation between Kurtosis and the optimal threshold is shown in Figure 3.7.

3.1 Adaptive Thresholding Using MLP:

An artificial neural network (ANN), usually called ”neural network” (NN), is a mathematical model or computational model based on biological neural networks. It consists of an interconnected group of artificial neurons and processes information using a connectionist approach to computation. In most cases an ANN is an adaptive system that changes its structure based on external or internal information that flows through the network during the learning phase. The utility of artificial neural network models lies in the fact that they can be used to infer a function from observations. This is particu-

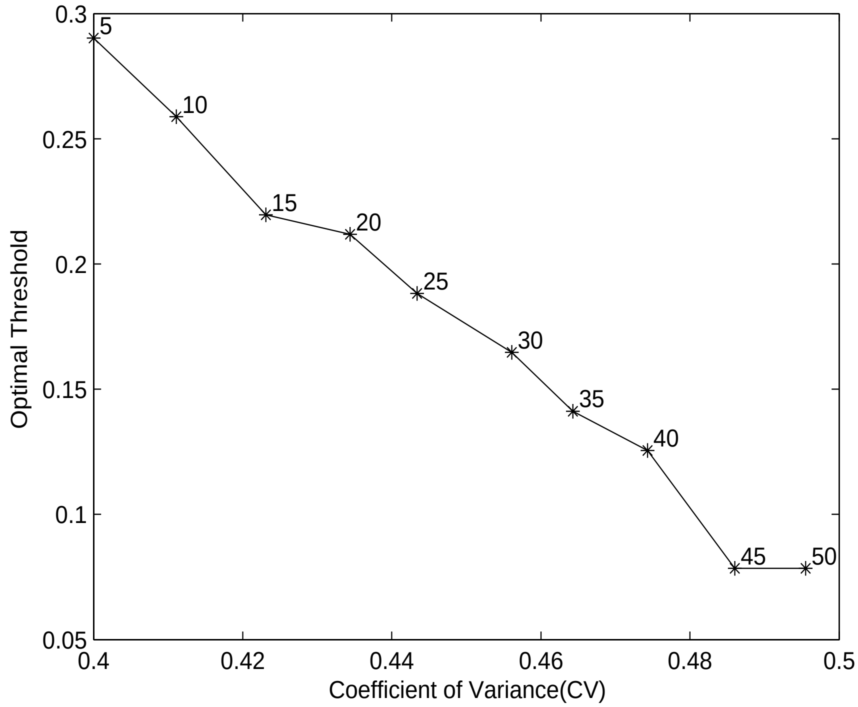


Figure 3.6: Variation of Optimal threshold with CV at different noise density for Lena image

larly useful in applications where the complexity of the data or task makes the design of such a function by hand impractical [12].

Artificial Neural Network (ANN) is a massively parallel distributed processor. It has a natural tendency to store knowledge and make them available for further use. ANN serves as a potential tool in numerous applications. The ANN based signal detection and filtering schemes are robust, accurate and work well under nonlinear situations.

An artificial neuron receives inputs from a number of other neurons or from external stimulus. A weighted sum of these inputs constitutes the arguments to a nonlinear activation function. The resulting value of the activation function is the output of the neuron. This output gets distributed along weighted connections to other neurons. The actual manner in which these connections are made defines the flow of information in the network and called architecture of the ANN. The method used to adjust the weights is the process of training the network is called the learning rule. The learning may be supervised or unsupervised [13]. Genuine neural networks are those with at least

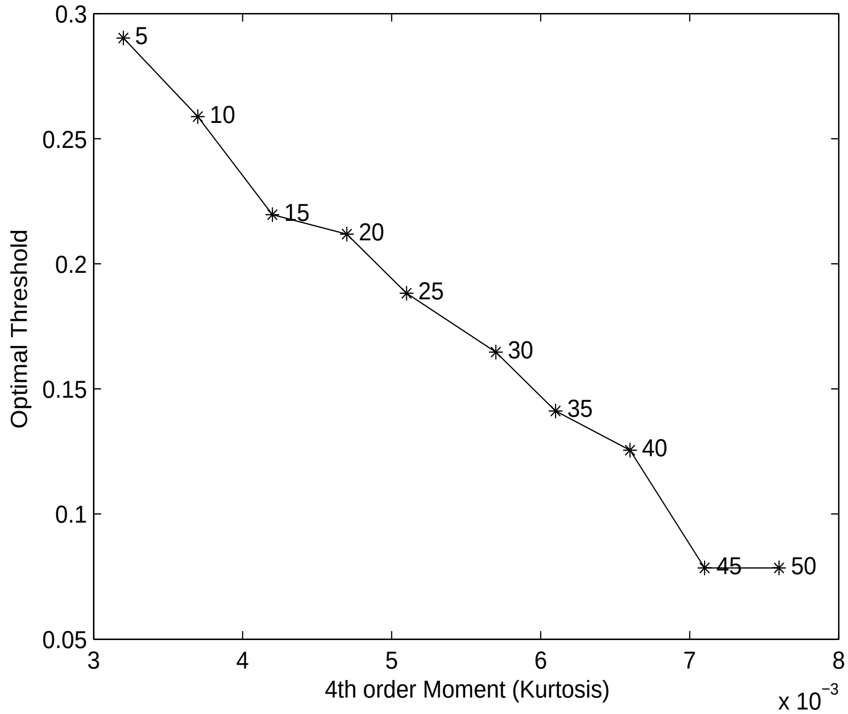


Figure 3.7: Variation of Optimal threshold with Kurtosis at different noise density for Lena image.

two layers of neurons – a hidden layer and an output layer. The hidden layer neurons should have nonlinear and differentiable activation functions. The nonlinear activation functions enable a neural network to be a universal approximator. The problem of representation is solved by the nonlinear activation functions [12].

Here in this section a simple 3-4-3-1 ANN (Figure 3.8) is used to adapt the image environment and to provide an optimal threshold value for impulsive noise detection. Both the noisy image characteristics (Section 3.2) mean (μ), variance (σ^2) and kurtosis (μ_4) of *Lena, Boat* and *Bridge* images are obtained. These three parameters along with corresponding Θ_{opt} of these three images are used here to train the suggested neural network using the conventional Back propagation algorithm. μ, σ^2 and μ_4 of the noisy image are the three inputs to the network and Θ_{opt} is the target output of the network. The training convergence characteristics of the network is obtained and shown in Figure 3.9

The neural networks with trained weights are used to obtained threshold subse-

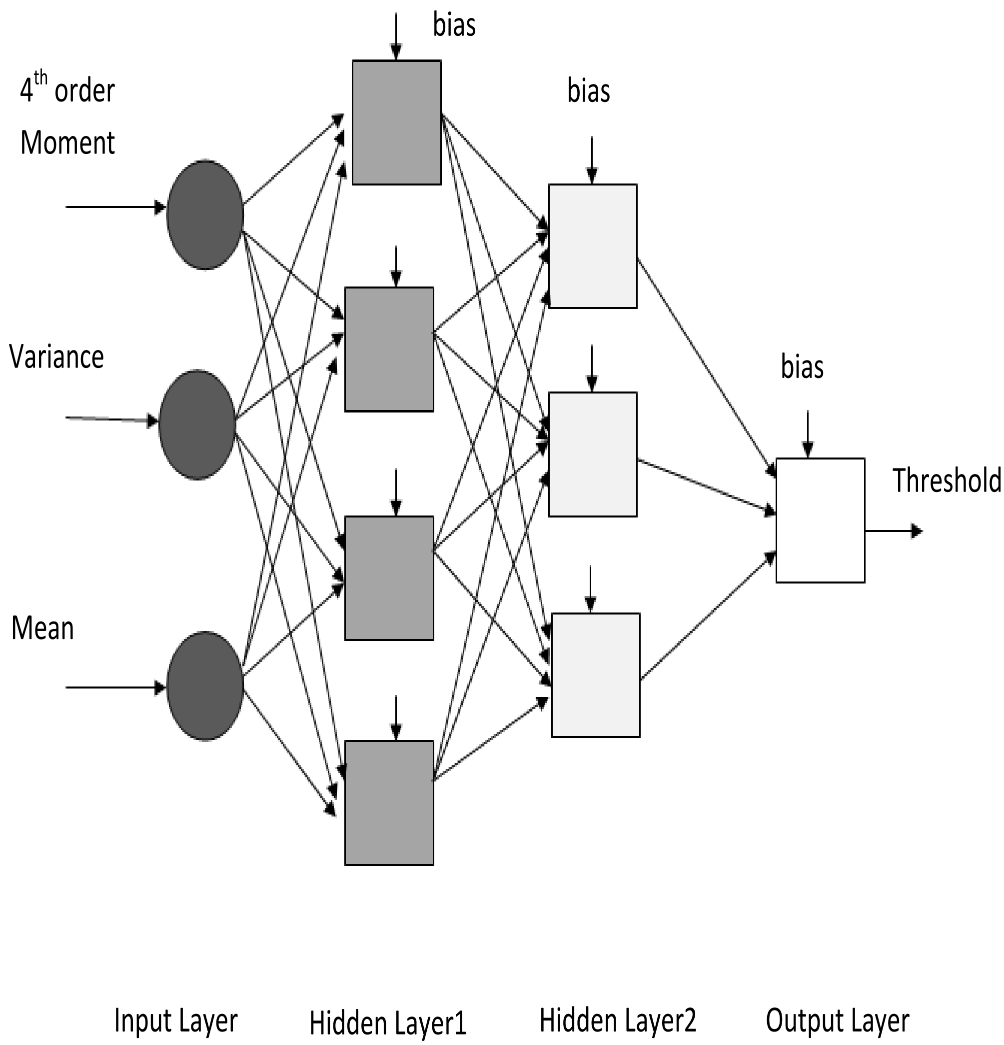


Figure 3.8: Multi-Layer Perceptron Structure of Threshold Estimator.

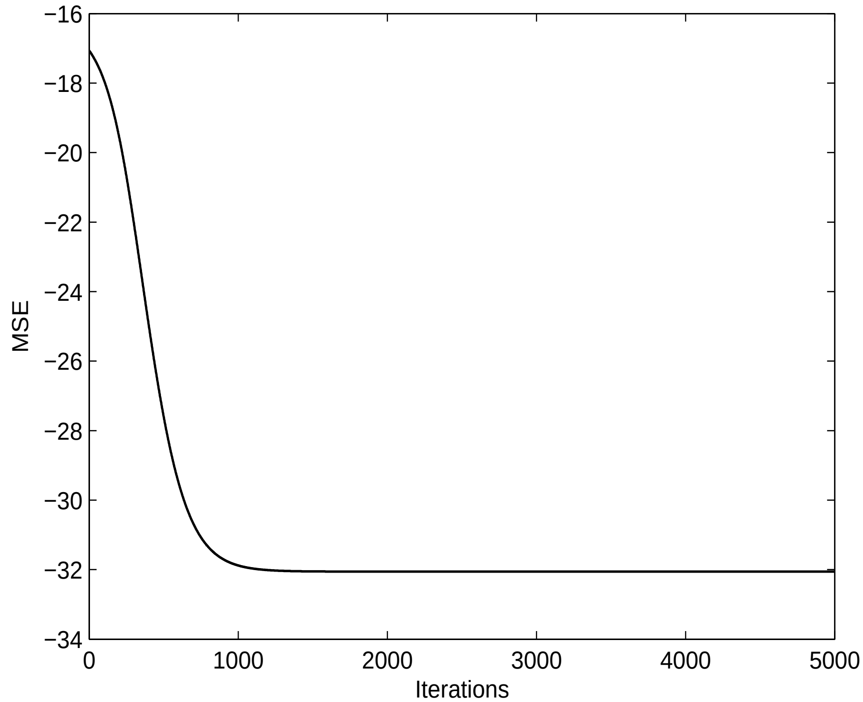


Figure 3.9: Convergence Characteristics of Multilayer Perceptron Network

quently. It is seen that the network predicts near to accurate threshold for images that are not used for training as well.

3.2 Summary

Detector utilises a threshold value to compare with a predefined parameter. Fixed threshold is not suitable and do not work well under different noise conditions as well as for different images. In this chapter, we have proposed adaptive threshold determination strategies based on given noisy image statistics. Various statistical parameters i.e. (μ, σ^2, μ^4) are also used to predict the threshold value. We utilise neural network model i.e. MLP for detection of adaptive threshold.

Chapter 4

Conclusion and Future Work

Chapter 4

Conclusion and Future Work

This thesis deals with the removal of Random-Valued Impulsive Noise (RVIN). Impulsive noise being contaminated in some pixels based on probability densities. Basically Impulsive noises are basically two types- Salt & Pepper Noise (SPN) and Random-Valued Impulsive Noise. In chapter we first try to distinguish between SPN and RVIN. Some previous schemes are most suitable to remove RVIN. Mostly performance of selective filtering scheme dependent on a impulse noise detector to decide where the pixel under study is noisy or not.

Next chapter we propose a new scheme to removal the RVIN from images. The proposed filter is an Impulsive noise removal scheme using double difference based detection and weighted median filter. In the detection phase, we introduce the direction wise double difference concept to detect a random-valued impulsive noise, basically it can distinguish a noise and an edge point nicely. Then contaminated pixel point is replaced by weighted median filter.

In addition detector utilises a threshold value to compare with a predefined parameter. Fixed threshold is not suitable and do not work well under different noise conditions as well as for different images. In this investigation, we have proposed adaptive threshold determination strategies based on given noisy image statistics. Various statistical parameters i.e. (μ, σ^2, μ_4) are also used to predict the threshold value. We utilise neural network model i.e. MLP for detection of adaptive threshold.

All the proposed schemes have been simulated using Matlab along with the well known previous filters. Standard images like Lena, Boat, Bridge etc. are chosen for simulation under similar condition for all schemes. Quantitative performance measurements like PSNR (dB) have been used to compare the schemes in restored images. Subjective performance has been used and shown with respect to restored images. It has been observed that the proposed scheme outperforms the existing schemes both in terms of noise rejection and retention of original image properties.

The proposed scheme has been performing well under images up to 40% noise densities. Further investigation can be made to study at high noise conditions. Further work can be extended to utilise other neural network model such as FLANN, RBFN for detection of adaptive threshold. Future work can be extended to reduce the false and miss detection count to improve the detector capability. To apply the proposed scheme in practical applications, parallel implementations of these schemes may be thrust upon.

Bibliography

[1] R C Gonzalez and R E Woods. *Digital Image Processing*. Prentice-Hall, India, second edition edition, 2007.

[2] B Chandra and D Dutta Majumder. *Digital Image Processing and Analysis*. Prentice-Hall, India, first edition edition, 2007.

[3] K. S. Srinivasan and D. Ebenezer. A new fast and efficient decision based algorithm for removal of high-density impulse noises. *IEEE Signal Process. Lett.*, 14(3):189–192, March 2007.

[4] Pankaj Kumar Sa. On the development of impulsive noise removal schemes. *M.Tech thesis NIT Rourkela*, 2006.

[5] T. Chen and H. R. Wu. Adaptive impulse detection using center-weighted median filters. *IEEE Signal Process. Lett.*, 8(1):1–3, January 2001.

[6] S. Ko and Y. Lee. Center weighted median filters and their applications to image enhancement. *IEEE Trans. Circuits Syst*, 38(9):984–993, September 1991.

[7] T. Chen and H. R.Wu. Space variant median filters for the restoration of impulse noise corrupted images. *IEEE Trans. Circuits Syst. II*, 48(8):784–789, August 2001.

[8] K.-K. Ma T. Chen and L.-H. Chen. Tri-state median filter for image denoising. *IEEE Signal Process. Lett*, 8(12):1834–1838, December 1999.

[9] V. Senk V. Crnojevic and Trpovski. Advanced impulse detection based on pixel-wise mad. *IEEE Signal Process. Lett*, 11(7):589–592, July 2004.

[10] S. K. Mitra E. Abreu, M. Lightstone and K. Arakawa. A new efficient approach for the removal of impulse noise from highly corrupted images. *IEEE Trans. Image Processing*, 5:1012–1025, June 1996.

[11] Y. Dong and S. Xu. A new directional weighted median filter for removal of random-valued impulse noise. *IEEE Signal Process. Lett*, 14(3):193–196, March 2007.

[12] Simon Haykin. *Neural Networks A Comprehensive Foundation*. Pearson Education, India, second edition edition, 2004.

[13] Banshidhar Majhi. Soft computing techniques for image restoration. *PhD thesis, Sambalpur University*, 2000.

Dissemination of Work

1. Aloke Datta, Pankaj Kumar Sa, Banshidhar Majhi ``Random-Valued Impulse Noise Filter Based on Second-Order-Difference ´´, *All India Conference AICON'09*, 6-8 February 2009, CSIT,Durg, India.

2. Aloke Datta, Pankaj Kumar Sa, Banshidhar Majhi ``An Impulse Noise Filter Using Second-Order-Difference Detection ´´, *National Conference on Recent Advances in Communication Technology* $NCRACT-2009$, 30 Jan - 1 Feb 2009, NIT, Rourkela, India.

3. Ratnakar Dash, Pankaj Kumar Sa, Member, IEEE, Aloke Datta, and Banshidhar Majhi, Member, IEEE ``Impulsive noise removal scheme from images using double difference based detection and weighted median filter ´´, *IEEE Signal Processing Letters* , $Communicated$