

Denoising Images Under Multiplicative Noise

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Denoising Images Under Multiplicative Noise

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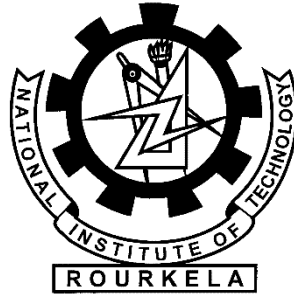
DEDICATED
TO
MY LOVING PARENTS, SISTERS, BROTHER-IN-LAWS AND
MY SWEET NEPHEWS WRITBAN AND KRISHANU

Declaration

I certify that

- The work contained in this thesis is original and has been done by me under the guidance of my supervisor.
- The work has not been submitted to any other Institute for any degree or diploma.
- I have followed the guidelines provided by the Institute in preparing the thesis.
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C E R T I F I C A T E

*This is to certify that the thesis entitled “**Denoising Images Under Multiplicative Noise**” by **Mr. Ayan Kanti Santra**, submitted to the National Institute of Technology, Rourkela (Deemed University) for the award of Master of Technology in **Electrical Engineering** with the specialization of “**Electronic Systems and Communication**”, is a record of bonafide research work carried out by him in the **Department of Electrical Engineering**, under my supervision. I believe that this thesis fulfills part of the requirements for the award of degree of Master of Technology. The results embodied in the thesis have not been submitted for the award of any other degree elsewhere.*

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Abstract

Generally the speckle noise occurred in images of different modalities due to random variation of pixel values. To denoise these images, it is necessary to apply various filtering techniques. So far there are lots of filtering methods proposed in literature which includes the Wiener filtering and Wavelet based thresholding approach to denoise such type of noisy images.

This thesis analyse exiting Wiener filtering for image restoration with variable window size. However this restoration may not exhibit satisfactory performances with respect to standard indices like Structural Similarity Index Measure (SSIM), Signal-to-Noise Ratio (SNR), Peak Signal to Noise Ratio (PSNR), and Mean Square Error (MSE). Literature indicates that Curvelet transform represents natural image better than any other transformations. Therefore, curvelet coefficient can be used to segment true image and noise.

The aim of the thesis to characterize the multiplicative noise in Curvelet transform domain. Subsequently a threshold based denoising algorithm has been developed using hard and MCET thresholding techniques.

Finally, the denoised image was compared with original image using some quantifying statistical indices such as SSIM, MSE, SNR and PSNR for different noise variance which The experimental results demonstrate its efficacy over Wiener filtering method.

Keywords: Multiplicative Noise, Wiener filtering, Curvelet transform, Image thresholding techniques, Statistical parameters.

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List of Abbreviations

Abbreviation	Description
SSIM	Structural Similarity Index
MSSIM	Mean Structural Similarity Index
SS-SSIM	Single-Scale Structural Similarity Index
MS-SSIM	Multi-Scale Structural Similarity Index
UQI	Universal image Quality Index
SNR	Signal-to-Noise-Ratio
PSNR	Peak-Signal-to-Noise-Ratio
MSE	Mean Square Error
RMS	Root Mean Squared Error
MAE	Mean Absolute Error
NCC	Normalized Cross Correlation Coefficient
NRCC	Non-linear Regression Correlation Coefficient
ROCC	Spearman Rank-Order Correlation Coefficient
OR	Outlier Ratio
STD	Standard Deviation(σ)
FDCT	Fast Discrete Curvelet Transform
IFDCT	Inverse Fast Discrete Curvelet Transform
GUI	Graphical User Interface
SAR	Synthetic Aperture Radar
US	Ultrasound

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Chapter 1

INTRODUCTION

1.1 Background

Image denoising is one of the most essential tasks in image processing for better analysis and vision. There are many types of noise which can decrease the quality of images. The Speckle noise which can be modeled as multiplicative noise, mainly occurs in various imaging system due to random variation of the pixel values. It can be defined as the multiplication of random values with the pixel values. Mathematically this noise is modeled as:

$$\text{Speckle noise} = I * (1 + N)$$

Where 'I' is the original image matrix and 'N' is the noise, which is mainly a normal distribution with mean equal to zero. This noise is a major problem in radar applications. Wiener filtering comes under the non-coherent type of denoising method, which is mainly used as a restoration technique for all type of noisy images [1]. However this filter do not giving promising result in terms of various quality performance measuring indices such as Structural Similarity Index Measure (SSIM), Mean-Square-Error (MSE), Signal-to-Noise Ratio (SNR) and Peak-Signal-to-Noise Ratio (PSNR) between original and restored image. Curvelet transform was introduced by E. J. Candes [2, 3]. It is a higher version of image representation at fine scales, and it is developed from Wavelet as multi-scale representation. Curvelet transform based algorithms

are widely used for image denoising. In Curvelet domain the large coefficients value are shown as original image signal and the small coefficients value shown as noise signal. In this research, we propose first discrete Curvelet transform with different thresholding methods such as Hard-thresholding and Minimum Cross Entropy Thresholding (MCET) for removal of speckles from image.

The proposed method consist of three parts, Curvelet transform(FDCT), Curvelet coefficients processing and inverse transform(IFDCT). In the first step Curvelet transform of noisy image is calculated which are thresholded by different thresholding function. Finally, inverse Curvelet transform is found to reconstruct denoising image. The reconstructed denoised image was compared with original image using SSIM, MSE, SNR and PSNR. An entropy-based thresholding [4, 5, 6] has been implemented in Curvelet domain for better result. The next modification can be use of clustering-based thresholding methods. Curvelet denoising technique is applied to any type of images like natural, satellite, medical like Computed Tomography (CT), Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET), Single Photon Emission Computed Tomography (SPECT), Ultrasonic images, etc.

1.2 Review of Literature

Many researchers, proposed various denoising technique like Wavelet based thresholding, Wiener filtering etc. The Curvelet transform is a recently introduced as non-adaptive multi-scale transforms that is mainly popular in the image processing field.

Kumar *et al.* [1] in 2010 proposed two filtering (Median and Wiener filters) algorithms to denoise image with different types of noise (Gaussian noise, Salt & Pepper noise and Speckle noise) that are either present in the image during capturing or injected into the image during transmission. Conclusion drawn from the paper was that, the performance of the Wiener filter after denoising for Speckle and Gaussian noisy image is better than Median filter. The performance of the Median filter after denoising for Salt & Pepper noisy

image is better than Wiener filter.

Candes *et al.* [2, 7] in 2006 describe the second generation Curvelet transform in two and three dimensions for image representation. They have introduced two methods for transformation as given, the first digital transformation is based on FDCT via unequally spaced fast fourier transforms, while the second is based on FDCT via wrapping. Those are differed by spatial grid used for translate Curvelets at each scale and angle. However, wrapping is better than USFFT, because of the wrapping method take less computational time than USFFT.

Starck *et al.* [3] in 2002 presented a strategy for digitally implementing for both transforms the Ridgelet and the Curvelet. Both the transformation techniques have the property of exact reconstruction which is stable in nature.

Huang *et al.* [8] in 2004 categorized a survey of image thresholding methods. In this literature we have observed that the clustering-based method of Kittler and Illingworth [9] and the entropy-based methods of Kapur, Sahoo, and Wong [10], and Sahoo, Wilkins, and Yeager [11], are the best performing thresholding algorithms. Similarly, the clustering-based method of Kittler and Illingworth [9] and the local-based methods of Sauvola and Pietaksinen [12] and of White and Rohrer are the best performing document binarization algorithms. However, these results are obtained only from text document images degraded with noise and blur. For example, the increasing number of color documents becomes a new challenge for binarization and segmentation. Multilevel thresholding, or simply multi-thresholding is gaining more applicability in vision applications. A few authors have addressed this issue in [13, 14, 15, 16, 17, 18, 19].

Sezgin *et al.* [8] in 2004 describe different image thresholding and compare between all thresholding technique. We have seen that authors are categorize the thresholding techniques in six group depend on there information. The categories are:

1. Histogram Shape-based Thresholding

2. Entropy-based Thresholding
3. Clustering-based Thresholding
4. Attribute Similarity-based Thresholding
5. Spatial Thresholding
6. Local Adaptive Thresholding

Literature suggests entropy-based and clustering-based thresholding both are providing better performance compared to other technique.

Amani *et al.* [5] in 2009 describe entropy-based image thresholding for image segmentation. This approach is derived from ‘Pal method’ [4] that segment images using minimum cross-entropy thresholding based on Gamma distribution instead of Gaussian distribution. Gamma distribution has ability of representing symmetric and non-symmetric histograms. This proposed method is tested by using Synthetic Aperture Radar (SAR) images and it gives reliable results for bi-modal and multi-modal images. This method is more general than Pal [4] method and experimental results on SAR images showed good results in thresholding.

Osaimi *et al.* [6] in 2008 presents a new algorithm for SAR image segmentation based on thresholding technique. Generally, segmentation of a SAR image falls under two categories; one based on grey levels and the other based on texture. This paper deals with SAR image segmentation based on grey levels and developed a new formula using Minimum Cross Entropy Thresholding (MCET) method for estimating optimal threshold value based on Gamma distribution to analyzing data of images; that means histogram of SAR images is assumed to be a mixture of Gamma distributions. It applied on both bi-modal and multi-modal images. The contributions of this method include an iterative programming technique that is proposed for reducing huge computations. The experimental results obtained are promising

and it encourage future research for applying this method to complex image processing and computer vision problems and applications.

1.3 Motivations

Multiplicative noise or speckle noise occurred in various imaging systems due to random variation of pixel values. Although a number of restoration techniques were proposed in literature like Wiener filtering and Lee filtering to denoise such kind of noisy images, however these methods are not giving promising results in terms of PSNR, MSE and SNR. In this present research, we use various thresholding techniques like hard thresholding and entropy based thresholding in curvlet domain to denoise these images. The objective of this research is given as:

1.4 Objectives of the Thesis

The salient objectives of the thesis are:

- Reduce multiplicative noise in images using different restoration techniques.
- Analysis of the denoising method in frequency domain using Wiener filtering.
- Implementation of the proposed denoising method in transform domain using different thresholding.
- Compared reconstructed image with original image using following statistical parameters- SSIM, SNR, PSNR and MSE for different noise variance.
- Development of a real-time image processing system using Matlab GUI.

1.5 Thesis Organisation

The thesis is organized as follows.

- Chapter 1, Introduction.
- Chapter 2, Images under Multiplicative Noise.
- Chapter 3, Multiplicative Noise.
- Chapter 4, Methodology of Image Denoising.
- Chapter 5, Performance Assessment.
- Chapter 6, Result and Discussions.
- Chapter 7, concludes the thesis. Extensions of the present work and future scopes for further work are also discussed therein.
- Bibliography.

Chapter 2

IMAGES UNDER MULTIPLICATIVE NOISE

2.1 Introduction

2.1.1 Synthetic Aperture Radar Image

Speckle is significant in Synthetic Aperture Radar (SAR) and Ultrasound imaging. SAR image is shown in figure: 2.1. Active Remote Sensing Satellite for earth observation capture two-dimensional (2-D) image. Range measurement and resolution are achieved in SAR in the same manner as most other radars: Range is determined by precisely measuring the time from transmission of a pulse to receiving from a target in the wave length range 1mm to 1m of electromagnetic spectrum. The simplest SAR range resolution is determined by the transmitted pulse width, i.e. narrow pulses yield fine range resolution.

Since SARs are much lower in frequency than optical systems, even moderate SAR resolutions require an antenna physically larger than the practical size carried by an airborne platform usually hundred meters long antenna lengths are often required. However, airborne radar could collect data while flying this distance and then process the data as if it came from a physically long antenna. The distance the aircraft flies in synthesizing the antenna is known as the synthetic aperture. A narrow synthetic beam width resulting

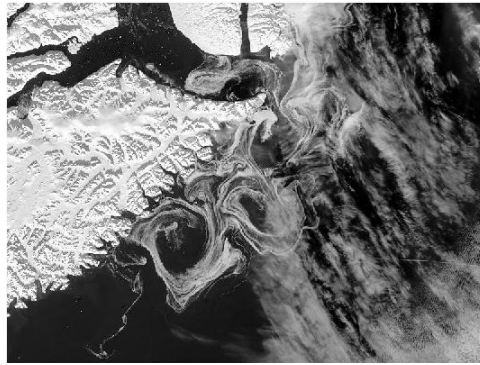


Figure 2.1: SAR image

from the relatively long synthetic aperture, yields finer resolution than the resolution possible from a smaller physical antenna. Achieving fine azimuth resolution may also be described from a doppler processing viewpoint. A target's position along the flight path determines the doppler frequency of its backscattering. Targets ahead of the aircraft produce a positive doppler offset, targets behind the aircraft produce a negative offset. The target's doppler frequency determines its azimuth position. While this section attempts to provide an intuitive understanding, SARs are not as simple as described above. Transmitting short pulses to provide range resolution is generally not practical.

Applications of Synthetic Aperture Radar Imaging:

The application of SAR imaging is increased day by day due to the development of new technologies and innovative ideas. The areas, where this imaging technique used are given as:

- Reconnaissance, Surveillance, and Targeting
- Treaty Verification and Nonproliferation
- Interferometry (3-D SAR)
- Navigation and Guidance
- Foliage and Ground Penetration

- Moving Target Indication
- Change Detection
- Environmental Monitoring

Speckle Noise in Satellite (SAR) Image

SAR is a coherent imaging technology that records both the amplitude and the phase of the back-scattered radiation as shown in figure: 2.2. An important feature that degrades SAR images quality is speckle noise. Speckle is a common noise-like phenomenon in all coherent imaging systems [20, 21]. Each resolution cell of the system contains many scatterers, the phases of the return signals from these scatterers are randomly distributed and speckle is due to the coherent nature of the sensor and the signal processing. The speckle noises will appear as bright or dark dots on the image and leads to limitation on the accuracy of the measurements given that the brightness of a pixel is determined not only by properties of the scatterers in the resolution cell, but also by the phase relationships between the returns from those scatterers. Speckle noise is multiplicative in nature, therefore speckle reduction techniques is essential before procedures such as automatic target detection and recognition, thus traditional filtering will not remove it easily. Speckle noise prevents automatically target recognition and texture analysis algorithm to perform efficiently and gives the image a grainy appearance. Hence, speckle filtering turns out to be a critical pre-processing step for detection or classification optimization. Degraded image with speckle noise in SAR imaging is given by the equation;

$$d(X,Y) = I(X,Y) * S(X,Y) \quad (2.1)$$

Where, $d(X,Y)$ is the degraded ultrasound image with speckle, $I(X,Y)$ is the original image and $S(X,Y)$ is the speckle noise. Where (X,Y) denotes the pixel location. The multiplicative nature of speckle complicates the noise reduction process [22].

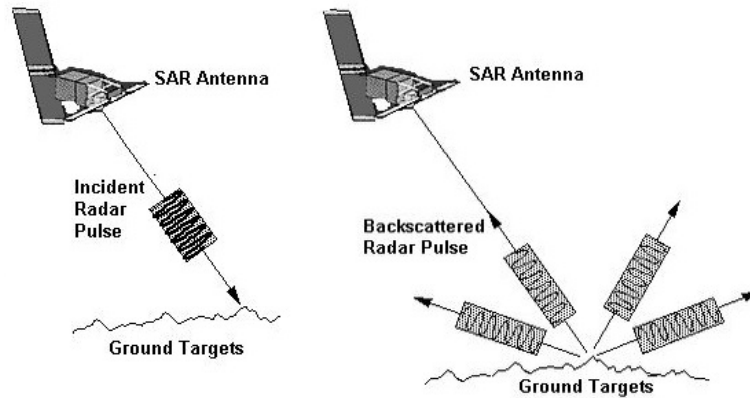


Figure 2.2: Complex case of microwave signal backscattering from multiple targets

2.1.2 Ultrasound Imaging

Introduction

It is a medical imaging technique that uses high frequency sound waves and their echoes. The technique is similar to the echolocation used by bats, whales and dolphins, as well as SONAR used by submarines. In ultrasound, the following events happen:

1. The ultrasound machine transmits high-frequency (1 to 5 megahertz) sound pulses into the human body using a probe.
2. The sound waves travel into the body and hit a boundary between tissues (e.g. between fluid and soft tissue, soft tissue and bone). Echoes are produced at any tissue interface where a change in acoustical impedance occurs. On these images, the film density is proportional to the intensity of the echo (a more energetic echo would produce a darker or lighter dot on the film). The intensity of the returning echo, that is the energy returned to the transducer, is determined by,
 - The magnitude of the change in the acoustical impedance at the echoing interface.
 - The characteristics of the intervening tissue, and

- The normality (perpendicularity) of the interface to the transducer.
 - The appearance of the echo on the film is also determined by the degree of amplification (gain) applied after the echo has been received by the transducer.
3. Hence some of the sound waves get reflected back to the probe, while some travel on further until they reach another boundary and get reflected.
 4. The reflected waves are picked up by the probe and relayed to the machine.
 5. The machine calculates the distance from the probe to the tissue or organ (boundaries) using the speed of sound in tissue (1,540 m/s) and the time of the each echo's return (usually on the order of millionths of a second).
 6. The machine displays the distances and intensities of the echoes on the screen, forming a two dimensional image.

These scans use high frequency sound waves which are emitted from a probe. The echoes that bounce back from structures in the body are shown on a screen as shown in figure: 2.3. The structures can be much more clearly seen when moving the probe over the body and watching the image on the screen. The main problem in these scans is the presence of speckle noise which reduces the diagnosis ability.



Figure 2.3: Ultrasonic image

Applications of Ultrasound Imaging

Ultrasound has been used in a different types of clinical settings, like obstetrics, gynecology, cardiology and in cancer detection. The main advantage of ultrasound is that certain structures can be observed without using radiation. Ultrasound is more faster than X-rays or other radiographic techniques. Here some applications of ultrasound in medical imaging system is describe below:

1. Obstetrics and Gynecology
2. Cardiology
3. Urology

In addition to these areas, there is a growing use for ultrasound as a rapid imaging tool for diagnosis in emergency rooms.

Speckle Noise in Ultrasound Image

Ultrasound imaging being inexpensive, nonradioactive, real-time and non-invasive, is most widely used in medical field. To achieve the best possible diagnosis it is important that medical images be sharp, clear and free of noise and artifacts[23]. However occurrence of speckle is a problem with ultrasound imaging. Speckle is the artifact caused by interference of energy from randomly distributed scattering [24, 25, 26, 27]. Speckle noise tends to reduce image resolution and contrast and blur important details, thereby reducing diagnostic value of this imaging modality. Therefore speckle noise reduction is an important prerequisite whenever ultrasound imaging is used. Denoising of ultrasound images however still remains a challenge because noise removal causes blurring of the ultrasound images. Sometimes physicians prefer to use original noisy images rather than filtered ones because of loss of important features while denoising. Thus appropriate method for speckle suppression is needed which enhances the signal to noise ratio while conserving the edges and lines in images.

Speckle is generally considered to be multiplicative in nature. Within each resolution cell a number of elementary scatterers reflect the incident wave towards sensor. The backscattered coherent waves with different phases undergo a constructive or a destructive interference in a random manner. The acquired image is thus corrupted by a random granular pattern, called speckle that delays the interpretation of the image content.

2.2 Chapter Summary

This chapter, discussed basic imaging systems which includes definition of image, type of imaging and there definition with application. The types of imaging requires capturing device like sensor and circuitry of scanner or digital camera, these image capturing device add extra information which is also called as noise. Noise is undesirable signal which is a random variation of brightness or color information in an image. There are various types of such noise which have been described in Chapter: 3.

Chapter 3

MULTIPLICATIVE NOISE

3.1 Introduction

Image Noise is random variation of brightness or color in an image. It can be produced by any circuitry such as sensor, scanner or digital camera. Image noise is an undesirable signal, it's produce by image capturing device that add extra information. In many cases, it reduces image quality and is especially significant when the objects being imaged are small and have relatively low contrast. This random variation in image brightness is designated noise. This noise can be either image dependent or image independent.

3.2 Speckle Noise

Speckle noise is multiplicative noise. This type of noise occurs in various imaging systems such as Laser, Medical, Optical and SAR imagery. The source of this noise is a form of multiplicative noise in which the intensity values of the pixels in the image are multiplied by random values. Speckle noise in image is serious issue, causing difficulties for image representation. It is caused by coherent processing of backscattered signals from multiple distributed targets. The fully developed speckle noise has the characteristic of multiplicative noise. Speckle noise in image is a multiplicative noise, it is in direct proportion to the local grey level in any area.

$$P(x,y) = a(x,y) \cdot b(x,y) \quad (3.1)$$

Here $a(x,y)$ is original signal and $b(x,y)$ is noise introduced into signal to produce the corrupted image $P(x,y)$. (x,y) represent the pixel location. Speckle noise follows a gamma distribution and it is given by:

$$F(g) = \frac{g^{\alpha-1}}{(\alpha-1)! a^\alpha} e^{-\frac{g}{a}} \quad (3.2)$$

Where, a^α is variance, g is gray level and $F(g)$ is Gamma distribution. The figure 3.1 below shows the plot of speckle noise gamma distribution.

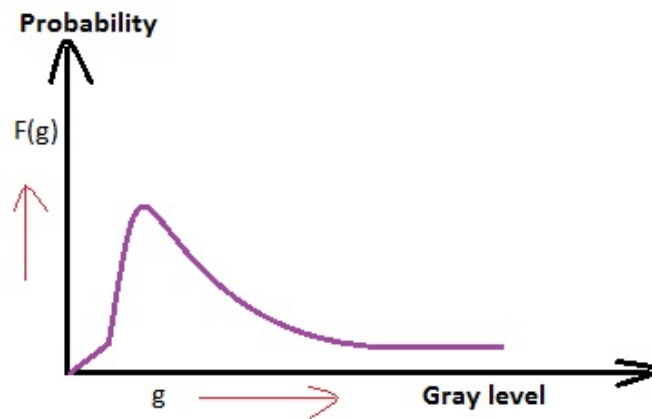


Figure 3.1: Probability density function of speckle noise model

It arises from random variations in the strength of the backscattered waves from objects and is seen mostly in RADAR and Ultrasound imaging.

Statistics of Speckle Noise

The pixel-to-pixel intensity variation in SAR images has a number of consequences; the most obvious one being that the use of a single pixel intensity value as a measure of distributed targets' reflectivity would be erroneous [22]. We know that the received signal is complex; let r and i denote its real and imaginary components. For a single-look SAR image, the intensity $I=r^2+i^2$ of a zone of constant reflectivity is exponentially distributed. The amplitude A , which is the square root of I , follows a Rayleigh distribution. For an

N-look image and independent looks, the intensity follows a Gamma distribution. There are several ways of obtaining N-look amplitude images in the spatial domain:

Case 1. Averaging N amplitude images;

Case 2. Averaging N intensity images, then taking the square root;

Case 3. Coherently averaging complex images by means of the Weighted Filter [23], then taking the square root.

In case 1, the probability density function is obtained by N convolutions of Rayleigh distributions, but cannot be expressed in analytic form. In the cases 2 and 3 it can be shown that the amplitude follows a K -distribution.

A usual way of characterizing the speckle level in SAR image is to compute $L = E^2(I) / \sigma^2(I)$ over an area of constant reflectivity; L is often called ENIL (Equivalent Number of Independent Looks) and gives no information on the spatial resolution of an image. We will also use the MSE between the ideal and noisy images (in the case where the ideal image is available), which reflects both speckle reduction and preservation of structures.

Model of Speckle Noise

An inherent characteristic of ultrasound imaging is the presence of speckle noise. Speckle noise is a random and deterministic in an image. Speckle has negative impact on ultrasound imaging, Radical reduction in contrast resolution may be responsible for the poor effective resolution of ultrasound as compared to MRI. In case of medical literatures, speckle noise is also known as texture. Generalized model of the speckle is represented as,

$$g(n,m) = f(n,m) * u(n,m) + \xi(n,m) \quad (3.3)$$

Where, $g(n,m)$ is the observed image, $u(n,m)$ is the multiplicative component and $\xi(n,m)$ is the additive component of the speckle noise. Here n and m denotes the axial and lateral indices of the image samples. In the ultrasound imaging consider only multiplicative noise and additive noise is

to be ignored. Hence, above equation can be modified as;
Therefore,

$$g(n,m) = f(n,m) * u(n,m) + \xi(n,m) - \xi(n,m)$$

$$g(n,m) = f(n,m) * u(n,m) \quad (3.4)$$

3.3 Image with Different Types Noise

Quality of an image is degraded by noise. Various type of noise can come into image with different strength. Some noisy images with different level of variance is shown in figure: 3.3.

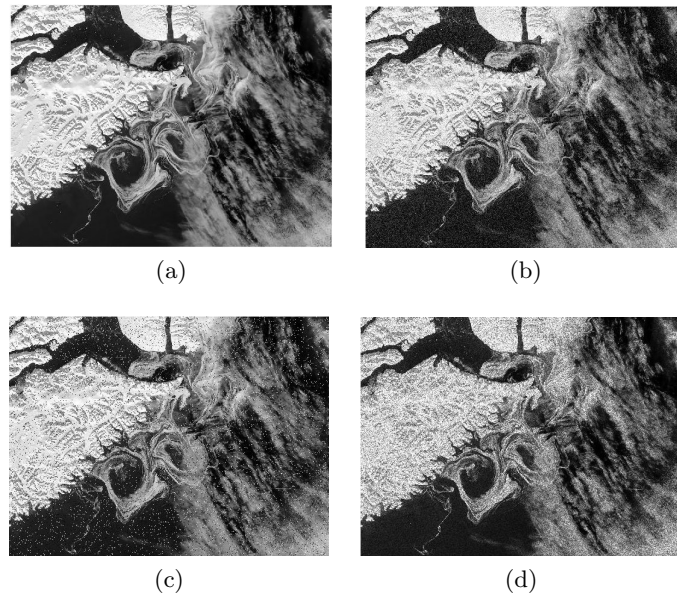


Figure 3.2: (a) Original SAR image, (b) Gaussian noisy SAR image with var. 0.02, (c) Salt and Pepper noisy SAR image with var. 0.05, (d) Speckle noisy SAR image with var. 0.08

3.4 Chapter Summary

This chapter, discussed noise in image which includes definition of noise, characteristics and major causes. The types of imaging requires capturing device like sensor and circuitry of scanner or digital camera, these image capturing device add extra information which is also called as noise. Noise is undesirable signal which is a random variation of brightness or color information in

an image. After addition of noise in an image, the image quality is degraded. So, removing noise from images first we analyse a restoration technique in frequency domain after proposed a restoration techniques in sparse domain for better vision. There are restoration techniques which can be used for denoising the multiplicative noisy image have been described in Chapter: 4.

Chapter 4

METHODOLOGY OF IMAGE DENOISING

4.1 Introduction

Image denoising is one of the most essential task in image processing. Two different technique of image restoration can be used for image denoising. These are Wiener filtering and various thresholding in Curvelet domain. Using some statistical parameter such as SSIM, MSE, SNR, PSNR we can calculate the amount of information retained in the denoising image compare to original image.

4.2 Simulation of Noisy Image

Synthetic Aperture Radar images have been taken from NASA (National Aeronautics and Space Administration) and ESA (European Space Agency). Here, We used satellite imagery (SAR) and standard image (Lena) for testing of different restoration techniques. These images are corrupted with uniformly distributed multiplicative noise having different levels of variance of the noise. By taking four different values of noise variances, four different SAR noisy images are being obtained. The range of noise variance are [0.04 0.08], where the variance 0.04 represents low level noisy image and variance 0.08 represents a high level noisy image.

4.3 Image Denoising Methods

This chapter we focus on two different techniques of image restoration, one is exiting Wiener filtering for analyses of denoising and other one is proposed in Curvelet domain with various thresholding [4, 5, 6, 28].

4.3.1 Image Denoising in Frequency Domain

For analyses the restoration process using Wiener filtering denoising the image when it is corrupted by speckle noise [1] with different variance.

Techniques Used for Image Denoising

- Wiener filtering
- Estimation of statistical parameters

Wiener Filtering

Wiener filter is a optimum linear filter which is involved only for linear estimation of a desired signal sequence. In the statistical approach to the solution of the Wiener filtering problem, we assume the statistical parameters of the useful signal and unwanted additive noise. The Wiener filter algorithm considers a signal $S_x(f)$ corrupted with noise $S_n(f)$. The noise has zero mean and variance of σ_n^2 . The resulting signal obtained after Wiener filtering be $H(f)$. The transfer function corresponding to Wiener filter was given by:

$$H(f) = \frac{S_{xy}(f)}{S_y(f)} = \frac{S_x(f)}{S_x(f) + S_n(f)} \quad (4.1)$$

This filter-optimization problem is to minimize the mean-square error of the signal that is defined by the actual filter output. This resulting solution is commonly known as the Wiener filter. The block diagram of a Wiener filter is shown in figure: 4.1,

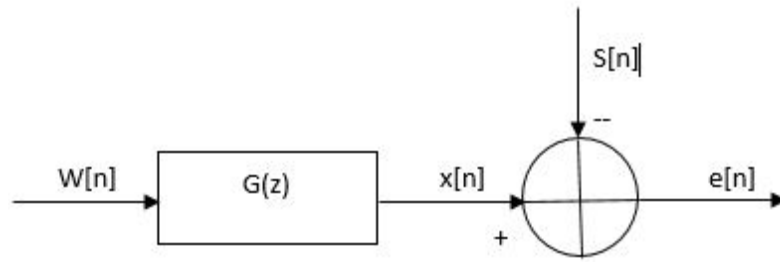


Figure 4.1: Block Diagram of Wiener Filtering to Denoise The Speckle Image.

Here,

$$G(Z) = \sum_{i=0}^N a_i Z^{-i}$$

$w[n]$ and $s[n]$ are random process signal. The filter output is $x[n]$ and $e[n]$ are the estimation error. An input signal $w[n]$ is convolved with the Wiener filter $G[z]$ and the result is compared to a reference signal $s[n]$ to obtain the filtering error $e[n]$. The image denoising using the Wiener filter is shown in the flowchart in figure 2.2.

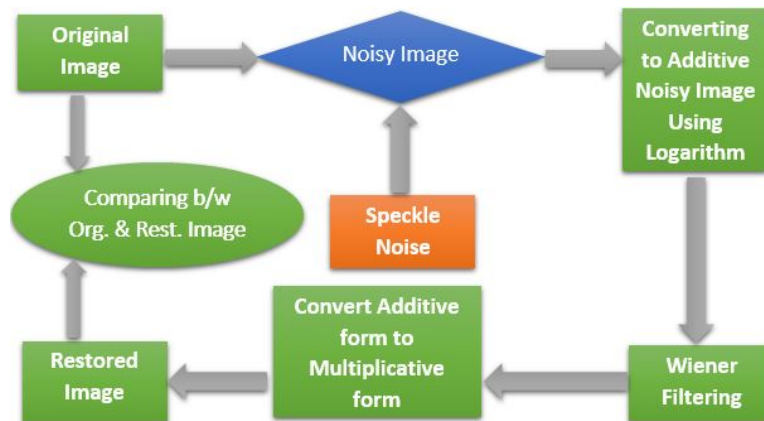


Figure 4.2: Flowchart of denoising algorithm using Wiener filtering.

Wiener Filter Characterization

Wiener filters are characterized by the following:

1. Assumption: signal and additive noise are casual processes with known spectral characteristics or known autocorrelation and cross-correlation.
2. Requirement: the filter must be physically realizable/causal.
3. Performance criteria: minimum mean-square error (MMSE).

This filter is frequently used in the process of deconvolution on the pixel of image using filtering window mask.

Advantage and Drawback of Wiener Filtering

The wiener filter expression is,

$$G(x, y) = \frac{H^*(x, y)}{|H(x, y)|^2 + \frac{S_n(x, y)}{S_f(x, y)}}$$

$$G(x, y) = \frac{H^*(x, y) \times S_f(x, y)}{|H(x, y)|^2 \times S_f(x, y) + S_n(x, y)} \quad (4.2)$$

Here,

- $H(x, y)$ = Degradation Function.
- $H^*(x, y)$ = Complex Conjugate of Degradation Function.
- $S_n(x, y)$ = Power Spectral Density of Noise.
- $S_f(x, y)$ = Power Spectral Density of Un-degraded Image.

Wiener filter is better for noise reduction because it uses statistical knowledge of the noise field. The transfer function of the Wiener filter is chosen to minimize the mean square error using statistical information on both image and noise field. The choice of window size of Wiener filter depends upon the noise variance of image.

Algorithm of Image Denoising Using Wiener Filtering

Here, we analyse an algorithm based on Wiener filtering for image denoising using logarithmic transformation.

1. Algorithm for denoising using Wiener filter:

Step 1: Take an original image.

Step 2: Add different variance of multiplicative(speckle) noise with original image.

Step 3: Convert the multiplicative noisy image into additive noisy image using logarithmic transformation.

Step 4: Applying the Wiener filtering to additive noisy image. Here, we using different size of Wiener filter mask. The mask size depending upon noise variance.

Step 5: Showing the restored image after Wiener filtering.

Step 6: Convert the restored image from additive to multiplicative form using anti-logarithmic transformation.

Step 7: Compare the restored image that obtained in step 6 with original image and estimate various statistical parameters like SSIM, SNR, MSE and PSNR, etc.

4.3.2 Image Denoising in Sparse/Transform Domain

After analyse wiener filtering, we proposed a restoration technique in sparse/transform domain using different thresholding techniques with logarithm or without logarithm for denoising the image [29, 3] with different noise variance.

Techniques Used for Image Denoising

- Curvelet Transform
- Thresholding
- Estimation of statistical parameters

Curvelet Transform

Curvelet transform was introduced by E. J. Candes [2]. On theoretical basis they are introduced two methods for transformation as given below:

- Unequispaced FFT Transform
- Wrapping Transform

Those are differ by spatial grid used for translate Curvelets at each scale and angle. However, wrapping algorithm provide faster computational technique or take less time than USFFT.

The idea of the Curvelet transform is first to decompose the image into Subband. The discrete Curvelet transform is mathematically expressed as:

$$c^D(j, l, k) = \sum_{0 \leq t_1, t_2 < n} f[t_1, t_2] \overline{\varphi_{j,l,k}^D[t_1, t_2]} \quad (4.3)$$

Where, $f[t_1, t_2]$ is 2D signal of cartesian arrays with $t_1 \geq 0$ and $t_2 < n$. $C^D(j, l, k)$ are Curvelet coefficients at scale j , location l and coordinates $k = (k_1, k_2) \in Z^2$, and $\varphi_{j,l,k}^D$ is a digital Curvelet waveform, here the superscript D is stands for digital. For detail follow in [2].

Advantage and Drawback of Curvelet Transform

The advantage of using curvelet are,

1. Curvelet approximate line singularity better than other transformation,
2. It is an optimal representation with edges.

The main drawback of the Curvelet transform is redundancy factor. It is redundant with a factor equal to $J+1$ for J scales.

Algorithm of Image Denoising in Curvelet Domain

Here, we proposed two different algorithm in Curvelet domain with two different thresholding methods like hard-thresholding and MCET thresholding

for image denoising, first algorithm is for image denoising in Curvelet domain using hard thresholding without logarithmic function and second one is with logarithmic function.

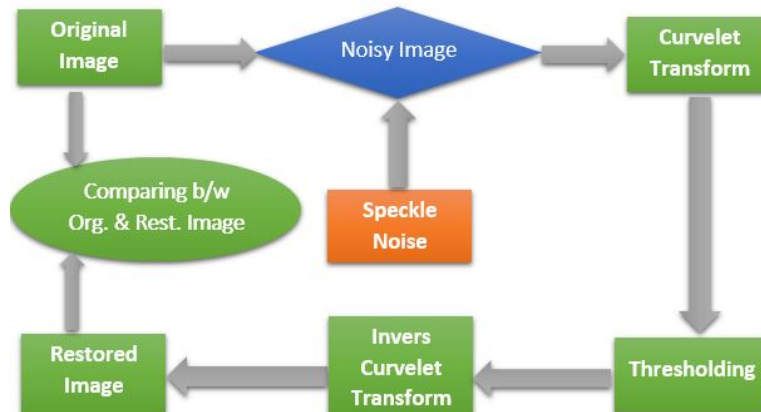


Figure 4.3: Flowchart of Curvelet transform algorithm for image denoising using hard-thresholding.

1. Algorithm for denoising in Curvelet domain using Hard thresholding:

Step 1: Take the original image.

Step 2: Add different variance of multiplicative (speckle) noise with original image.

Step 3: Apply the Curvelet transformation of noisy image.

Step 4: Apply different thresholding approach over the Curvelet coefficient.

Step 5: Applying inverse Curvelet transformation to obtain the restored image over the thresholded Curvelet coefficient.

Step 6: Calculate the information retained in the denoised image using statistical indices such as SSIM, SNR, MSE and PSNR.

1. Algorithm for denoising in Curvelet domain using Hard thresholding with Logarithm function:

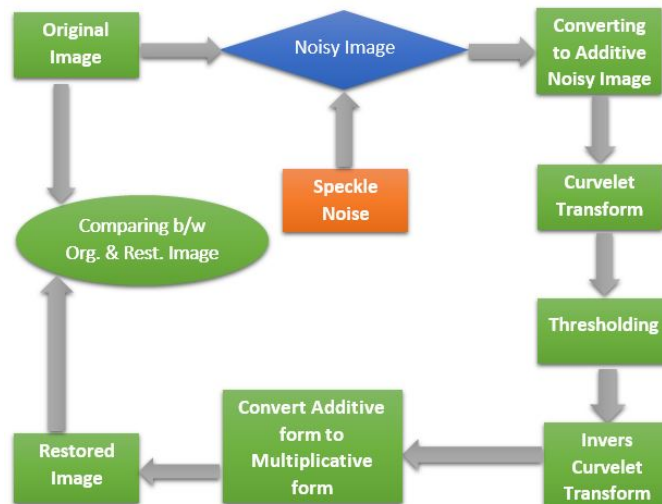


Figure 4.4: Flowchart of Curvelet transform algorithm for image denoising using hard-thresholding with logarithm.

Step 1: Take the original image.

Step 2: Add different variance of multiplicative(speckle) noise with original image.

Step 3: Convert the multiplicative noisy image into additive noisy image using logarithmic transformation.

Step 4: Apply the Curvelet transformation on noisy image.

Step 5: Apply different thresholding approach over the Curvelet coefficient.

Step 6: Applying inverse Curvelet transformation to obtain the restored image over the thresholded Curvelet coefficient.

Step 7: Convert the restored image from additive to multiplicative form using anti-logarithmic transformation.

Step 8: Calculate the information retained in the denoised image using statistical indices such as SSIM, SNR, MSE and PSNR.

4.3.3 Image Thresholding

Thresholding is one of the most effective technique for image segmentation. It is a non-linear operation that converts a binary image from a gray-scale image. Where the two levels are assigned for pixels that are below or above the specified threshold value. In many applications, it is useful to separate out the regions of the image corresponding to objects and background in which we want to analyze. Thresholding often provides an easy and convenient way to perform this segmentation on the basis of the different intensities or colors in the foreground and background regions of an image.

Why to Use Thresholding?

- The simplest segmentation method.
- Separate out regions of an image to objects which we want to analyze. This separation is based on the variation of intensity between the object pixels and the background pixels.

How to Select Threshold Value

A gray scale image and its corresponding histogram are shown below:

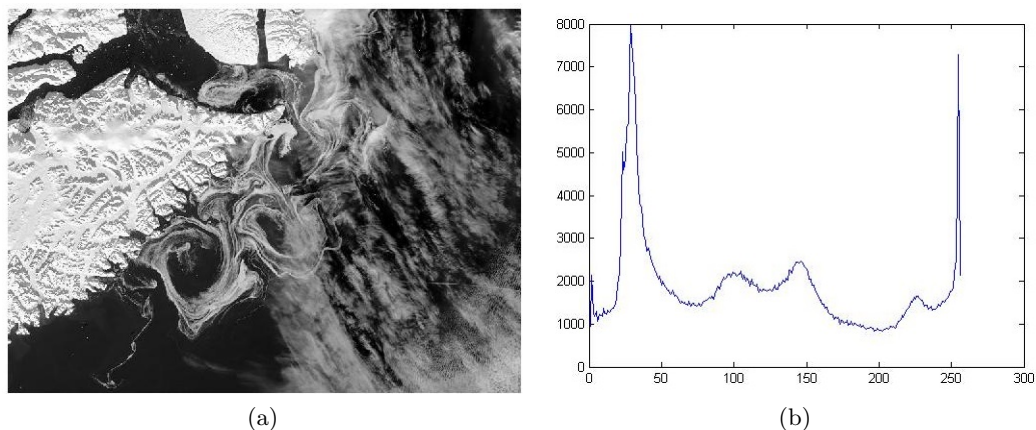


Figure 4.5: (a) Gray scale SAR image, (b) Histogram of corresponding gray scale SAR image

Looking at the picture figure: 4.5 on left, there are no white pixel value(255) and we can see that the histogram with this observation. So, select an accu-

rate threshold value from the histogram above that the most dominate (high to peak value of histogram) pixel value. So, if we select threshold value of '40', then every pixel value below the threshold is black and above the threshold is white. After the threshold we will get the following binary image.



Figure 4.6: Binary image of corresponding gray seal image.

Types of Thresholding

Different types of thresholding are used for denoising image. Threshold can be chosen by manually and automatically. It can be categorized into two groups, global and local threshold. Global thresholding technique, thresholds the complete image with a single threshold value and in local thresholding technique, segment the image into a number of sub-image and use a different threshold value for each sub-image. Global thresholding methods are easy to implement and faster because it take less computational time. Basic thresholding methods which is use for image segmentation these are:

- i. Automatical calculation of threshold value using an iterative method.
- ii. Hard Thresholding.
- iii. Soft Thresholding.
- iv. Adaptive Thresholding.
- v. Approximate the histogram of the image and choose a mid-point value of histogram as the threshold level.

In [8] thresholding methods are categorized in six different groups depends on the information they are exploiting. These categories are:

- a. Histogram shape-based methods.
- b. Clustering-based methods.
- c. Entropy-based methods.
- d. Objective attribute-based methods.
- e. Spatial information-based methods.
- e. Local adaptive methods.

We derived the two different methods of thresholding like hard thresholding and entropy-based thresholding using for image denoising.

Hard Thresholding

Hard-thresholding is a type of global thresholding, in this thresholding method thresholds the complete image with a single threshold value. So using that method for image denoising select one threshold value for whole image. Hard thresholding sets to zero those element whose absolute value is lower than the threshold value and neglecting zero element. Hard thresholding function is as follows:

$$f(y) = \begin{cases} y, & |y| > \lambda \\ 0, & |y| \leq \lambda \end{cases} \quad (4.4)$$

Where, y and $f(y)$ are the Curvelet coefficients before and after hard threshold processing, λ is a threshold value.

Entropy-based Thresholding

Entropy is measure of the uncertainty in a random variable. Image entropy is a quantity which is used to describe the amount of information retained in an image. The entropy or average information of an image can be determined

approximately from the histogram of the image. The histogram shows the different gray level probability in the image [30, 31].

Entropy Thresholding

Entropy thresholding is a means of thresholding an image that selects an optimum threshold value by choosing the pixel intensity from image histogram that show the maximum entropy over the entire image [10, 32, 33].

Type of Entropy Thresholding

1. Entropic Thresholding.
2. Cross-entropic Thresholding.
3. Fuzzy-entropic Thresholding.

Cross-entropic Thresholding

Cross entropy is a type of information theoretic distance between two probability distribution, it also known as divergence or cross-entropy [28, 4, 6].

Let, two probability distribution $P = (P_1, P_2, \dots, P_n)$ and $Q = (Q_1, Q_2, \dots, Q_n)$. So, Cross-entropy define,

For symmetric version can be written as:

$$D_S(P, Q) = \sum_{i=1}^S p_i \log \frac{p_i}{q_i} + \sum_{i=S+1}^L q_i \log \frac{q_i}{p_i} \quad (4.5)$$

For asymmetric version can be written as:

$$D_S(P, Q) = \sum_{i=1}^S p_i \log \frac{p_i}{q_i} \quad (4.6)$$

where,

1. i is gray-level(1,2,...,L) value.

2. P_i is probability of occurrence of gray-level.

3. $p_i = \frac{h_i}{M \times N}$

4. h_i is frequency of gray-level.

Assumed threshold S partitions the image into two regions, object and background. Let, S assume the the gray value(0 to S) assigned for object and ($(S+1)$ to L) assigned for background. Now describe the cross-entropy of segmented image with threshold S ,

$$D(S) = \sum_{i=1}^S ih_i \log \frac{i}{\mu_1(S)} + \sum_{i=S+1}^L ih_i \log \frac{i}{\mu_2(S)} \quad (4.7)$$

where, Average intensity value of foreground,

$$\mu_1(S) = \frac{\sum_{i=1}^S (ih_i)}{\sum_{i=1}^S h_i} \quad (4.8)$$

Average intensity value of background,

$$\mu_2(S) = \frac{\sum_{i=S+1}^L (ih_i)}{\sum_{i=S+1}^L h_i} \quad (4.9)$$

4.4 Chapter Summary

This chapter discusses various restoration techniques of multiplicative noisy image. The restoration is done by Wiener filtering in frequency domain. The restored image may be blurred if the windows size of Wiener filter is large. This means that part of information a true image has also been loss along with noise. These mask size of Wiener filter are varied depending upon the presence of noise variance in an image. The advantages and drawbacks of Wiener filtering are describe in section 4.3.1.

To overcome this drawback, a novel image denoising algorithm in sparse/transform domain using different thresholding techniques has been proposed. The performance of the algorithm can be judged using SSIM, MSE, SNR, PSNR. These parameters have been described in Chapter: 5.

Chapter 5

PERFORMANCE ASSESSMENT

5.1 Introduction

The parameters which are used in the filter performance evaluation are Signal to Noise Ratio (SNR), Mean Square Error (MSE), Peak Signal to Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM) [34, 35].

5.1.1 Measurement of SNR

Signal-to-noise ratio (SNR or S/N) is defined as signal power to noise power of the corrupting signal. It is one of the most essential statistical parameter for quality measurement of an image or signal. When a ratio higher than 1:1 then it indicates more signal power than noise power, it guarantees lower distortion and less interference cause by presence of noise. It can be derived from the formula,

$$SNR = \frac{P_{signal}}{P_{noise}} \quad (5.1)$$

where, P_{signal} is the signal mean or expected value and P_{noise} is the standard deviation of the noise.

5.1.2 Measurement of MSE

MSE is define as the average of square of the error. Where error is the differen between desire quantity and estimated quantity. The MSE provides a means of choosing the best estimator. We also calculate Root Mean Square

Deviation taking the square root of MSE, it is also good statistic parameter for measure quality of image. Having a Mean Square Error of zero (0) is ideal. The MSE is defined as:

$$MSE = \sum_{i=j=1}^N [f(i,j) - F(i,j)]^2 / N^2 \quad (5.2)$$

5.1.3 Measurement of PSNR

The Peak Signal-to-Noise Ratio (PSNR) [36] is define as a ratio between the maximum possible power of a signal and the noise power that affects the fidelity of its representation. PSNR is usually expressed in terms of the logarithmic decibel scale. The PSNR is most commonly used as a measure of quality of reconstruction of lossy compression for image compression. It is most easily defined via the mean squared error (MSE) which for two $m \times n$ monochrome images I and K where one of the images is considered a noisy approximation of the other is defined as:

$$MSE = \sum_{i=j=1}^N [f(i,j) - F(i,j)]^2 / N^2$$

The PSNR is defined as:

$$PSNR = 10 \log_{10} \left(\frac{MAX_I^2}{MSE} \right) = 20 \log_{10} \left(\frac{MAX_I}{MSE} \right) \quad (5.3)$$

Here, MAX_I is the maximum possible pixel value of the image. When the pixels are represented using 8 bits per sample, this is 255. More generally, when samples are represented using linear PCM with B bits per sample, MAX_I is $2^B - 1$.

5.1.4 Measurement of SSIM

The SSIM is an index that measure the similarity between two images. Recently the SSIM approach for image quality assessment [36]. The SSIM is

calculated on various windows of an image. Let, the measure between two windows f and g . This window is common size metric $N \times N$.

$$SSIM(f, g) = l(f, g)^\alpha \cdot c(f, g)^\beta \cdot s(f, g)^\gamma$$

Where, $\alpha > 0$, $\beta > 0$, $\gamma > 0$

$$SSIM(f, g) = \frac{(2\mu_f\mu_g + c_1)(2\sigma_f\sigma_g + c_2)}{(\mu_f^2 + \mu_g^2 + c_1)(\sigma_f^2 + \sigma_g^2 + c_2)} \quad (5.4)$$

Where,

- μ_f = The average of f .
- μ_g = The average of g .
- σ_f^2 = The Variance of f .
- σ_g^2 = The Variance of g .
- σ_{fg} = The Covariance of f and g
- $c_1 = (k_1, L)^2$ and $c_2 = (k_2, L)^2$ two variables that stabilize the division with weak denominator.
- L is the dynamic range of pixel value and $k_1 = 0.01$ and $k_2 = 0.03$ by default value.

We can also measured some image quality assessment such as MSSIM (Mean Structural Similarity Index), UQI (Universal image Quality Index) [37], SS-SSIM (Single-Scale Structural Similarity Index), MS-SSIM (Multi-Scale Structural Similarity Index), MAE (Mean Absolute Error), RMS (Root Mean Squared Error), NCC (Non-linear regression Correlation Coefficient), ROCC (Spearman Rank-Order Correlation Coefficient), OR (Outlier Ratio), STD (Standard Deviation(σ)) between restored image and original image for compressions [34].

5.2 Chapter Summary

This chapter discussed various statistical parameters and quality performance measuring index for measuring quality of an images. These parameters can be used for quality measurement and statistical information between original image and restored image after different restoration techniques. The results of all restoration techniques have been described in Chapter: 6.

Chapter 6

RESULT & DISCUSSIONS

6.1 Introduction

In this chapter, results of two different image restoration techniques are presented. First one is analysis of Wiener filter based method and the second one is proposed method in sparse/ transform domain using hard thresholding with and without logarithm function. The statistical parameters are computed for original and restored as well as original and noisy images. A comparative result is presented

6.1.1 Original Image with Different Noise Variance

Original Image with Different Noise Variance for Standard Image(Lena)



Figure 6.1: (a) Original image, 512 by 512, 8bits/pixel,with $MSE = 0$, $PSNR = \infty$, (b) Speckle noisy image with var. 0.04, (c) Speckle noisy image with var. 0.06, (d) Speckle noisy image with var. 0.08

Original Image with Different Noise Variance for Satellite Imagery(SAR)

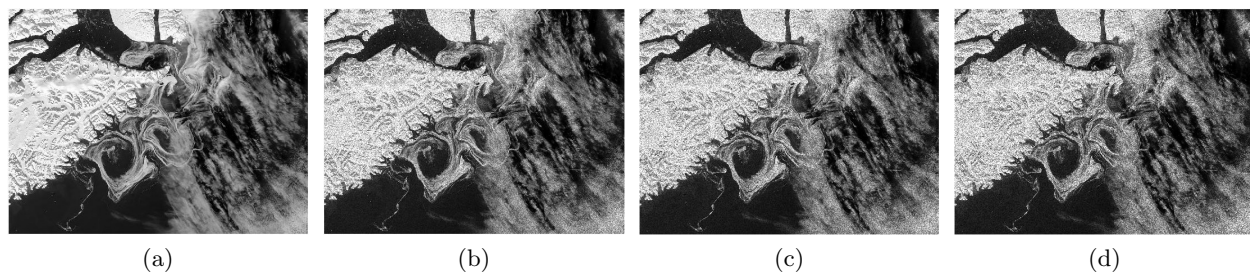


Figure 6.2: (a) Original image, 600 by 800, 8bits/pixel,with $MSE = 0$, $PSNR = \infty$, (b) Speckle noisy image with var. 0.04, (c) Speckle noisy image with var. 0.06, (d) Speckle noisy image with var. 0.08

6.1.2 Experimental Results of Denoising Image in Frequency Domain using Wiener Filter

Denoised Standard Image(Lena) in Frequency Domain using Wiener Filtering with Different Noise Variance



Figure 6.3: (a) Original image, 512 by 512, 8bits/pixel,with $MSE = 0$, $PSNR = \infty$, (b) Restored image of noise var. 0.04, (c) Restored image of noise var. 0.06, (d) Restored image of noise var. 0.08

Denoised Satellite Imagery(SAR) in Frequency Domain using Wiener Filtering with Different Noise Variance

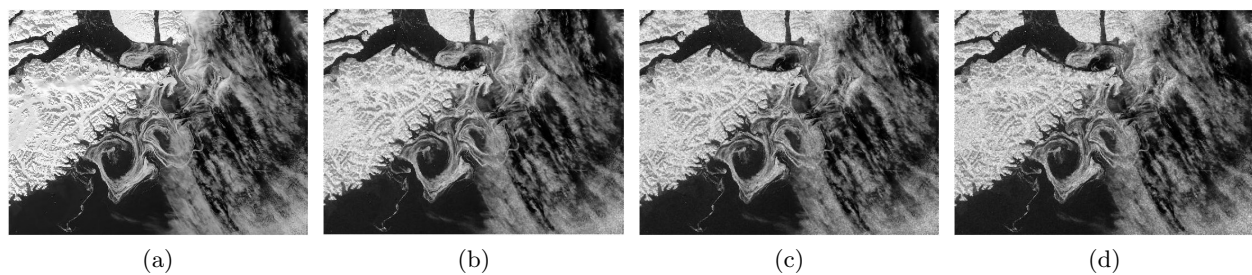


Figure 6.4: (a) Original image, 600 by 800, 8bits/pixel,with $MSE = 0$, $PSNR = \infty$, (b) Restored image of noise var. 0.04, (c) Restored image of noise var. 0.06, (d) Restored image of noise var. 0.08

For Standard Image(Lena)

Table 6.1: Comparison between original, noisy and restored image of Wiener filtering with different noise variance

Noise Variance	Statistical Parameter Indices	<i>OriginalImage</i> V_s <i>NoisyImage</i>	<i>OriginalImage</i> V_s <i>RestorImage</i>
0.04	SSIM	0.6082	0.8340
	MSE	687.8208	129.9290
	SNR	3.1938	6.7864
	PSNR	19.7900	27.0277
0.06	SSIM	0.5440	0.8097
	MSE	1013.4	158.7002
	SNR	2.7654	15.9708
	PSNR	18.1069	26.1590
0.08	SSIM	0.5015	0.7879
	MSE	1327.4	192.2015
	SNR	2.5371	5.8259
	PSNR	16.9347	25.3272

For Satellite Imagery(SAR)

Table 6.2: Comparison between original, noisy and restored image of Wiener filtering with different noise variance

Noise Variance	Statistical Parameter Indices	<i>OriginalImage</i> V_s <i>NoisyImage</i>	<i>OriginalImage</i> V_s <i>RestorImage</i>
0.04	SSIM	0.8557	0.8306
	MSE	573.633	401.677
	SNR	3.5445	3.8272
	PSNR	20.5785	22.7902
0.06	SSIM	0.8111	0.8141
	MSE	839.5793	461.636
	SNR	3.6298	3.61602
	PSNR	18.9242	21.5218
0.08	SSIM	0.77325	0.7987
	MSE	1106.3	526.611
	SNR	2.9457	3.2658
	PSNR	17.7462	20.9499

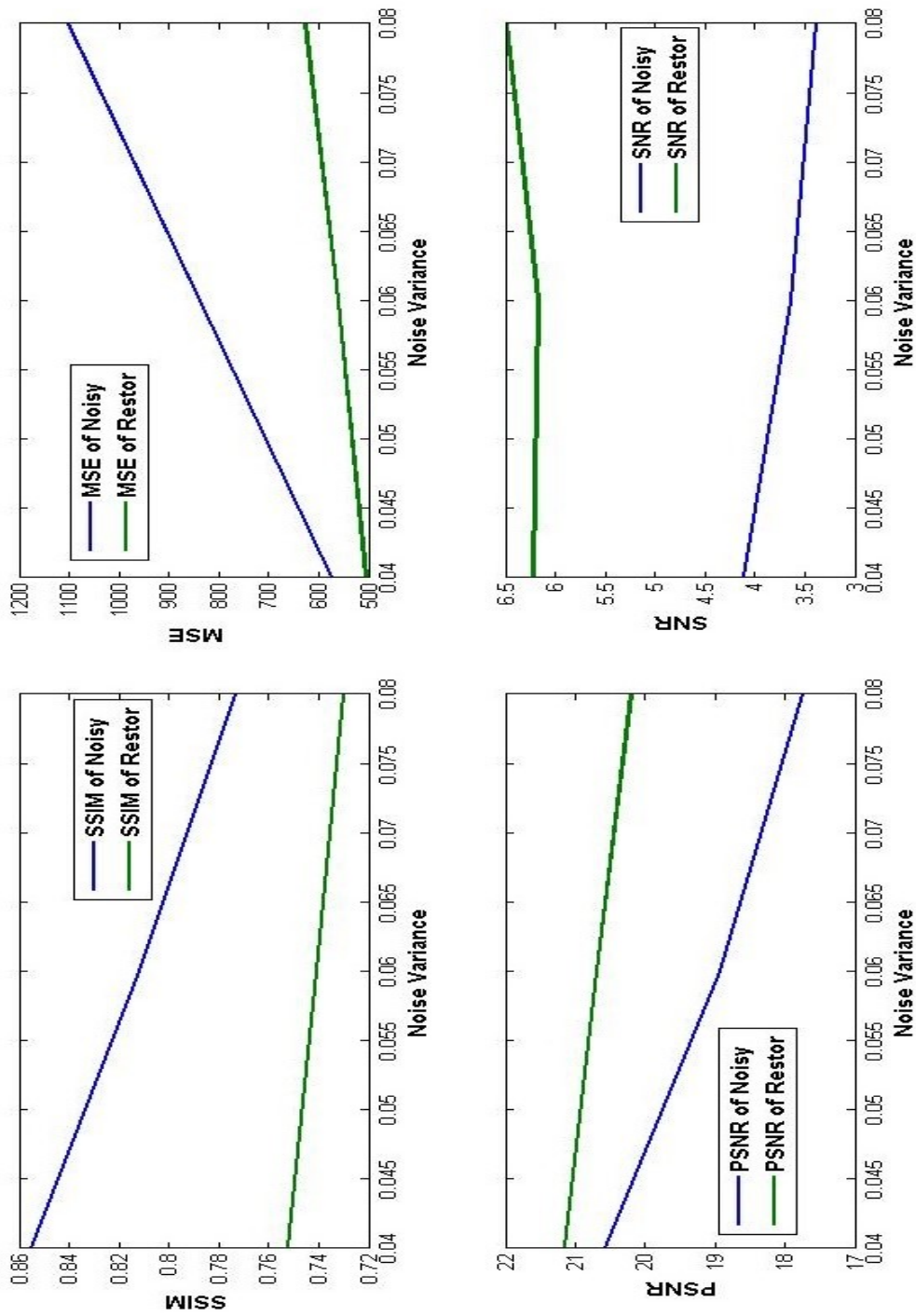


Figure 6.5: Statistical parameters Vs noise variance of Wiener filtering

6.1.3 Experimental Results of Denoising Image in Sparse/Transform Domain

Experimental Results of Denoising Image in Sparse/Transform Domain without Logarithm

Denoised Standard Image(Lena) in Sparse/Transform Domain with Different Noise Variance using Hard-thresholding



Figure 6.6: (a) Original image, 256 by 256, 8bits/pixel,with $MSE = 0$, $PSNR = \infty$, (b) Restored image of noise var. 0.04, (c) Restored image of noise var. 0.06, (d) Restored image of noise var. 0.08

Denoised Satellite Imagery(SAR) in Sparse/Transform Domain with Different Noise Variance using Hard-thresholding

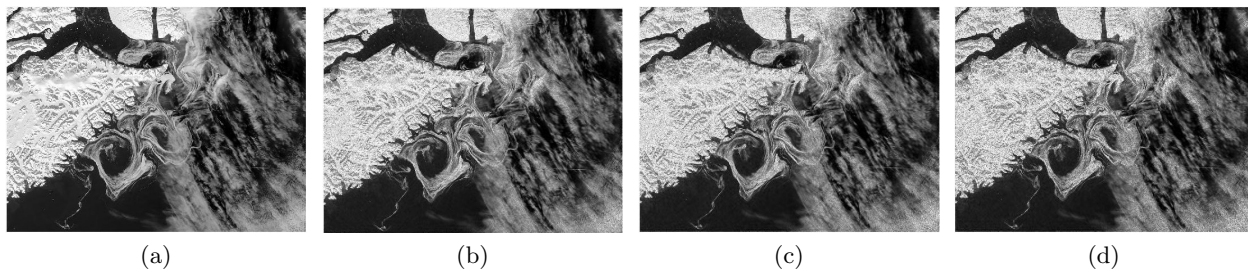


Figure 6.7: (a) Original image, 600 by 800, 8bits/pixel,with $MSE = 0$, $PSNR = \infty$, (b) Restored image of noise var. 0.04, (c) Restored image of noise var. 0.06, (d) Restored image of noise var. 0.08

For Standard Image(Lena)

Table 6.3: Comparison between original, noisy and restored image of Sparse/Transform domain using Hard-thresholding; with different noise variance

Noise Variance	Statistical Parameter Indices	<i>OriginalImage</i> <i>Vs</i> <i>NoisyImage</i>	<i>OriginalImage</i> <i>Vs</i> <i>RestorImage</i>
0.04	SSIM	0.6082	0.8766
	MSE	687.8208	73.0893
	SNR	3.1938	9.1034
	PSNR	19.7900	29.5263
0.06	SSIM	0.5440	0.8546
	MSE	1013.4	93.5340
	SNR	2.7654	8.4720
	PSNR	18.1069	28.4551
0.08	SSIM	0.5015	0.8337
	MSE	1327.4	108.7314
	SNR	2.5371	8.0055
	PSNR	16.9347	27.8012

For Satellite Imagery(SAR)

Table 6.4: Comparison between original, noisy and restored image of Sparse/Transform domain using Hard-thresholding; with different noise variance

Noise Variance	Statistical Parameters Indices	<i>OriginalImage</i> <i>Vs</i> <i>NoisyImage</i>	<i>OriginalImage</i> <i>Vs</i> <i>RestorImage</i>
0.04	SSIM	0.8557	0.8655
	MSE	573.6331	306.713
	SNR	3.5445	4.4851
	PSNR	20.5785	23.2975
0.06	SSIM	0.8111	0.8222
	MSE	839.5793	385.23
	SNR	3.6298	4.0748
	PSNR	18.9242	22.3076
0.08	SSIM	0.7732	0.8072
	MSE	1100.43	509.91
	SNR	2.9457	3.8997
	PSNR	17.7492	21.6142

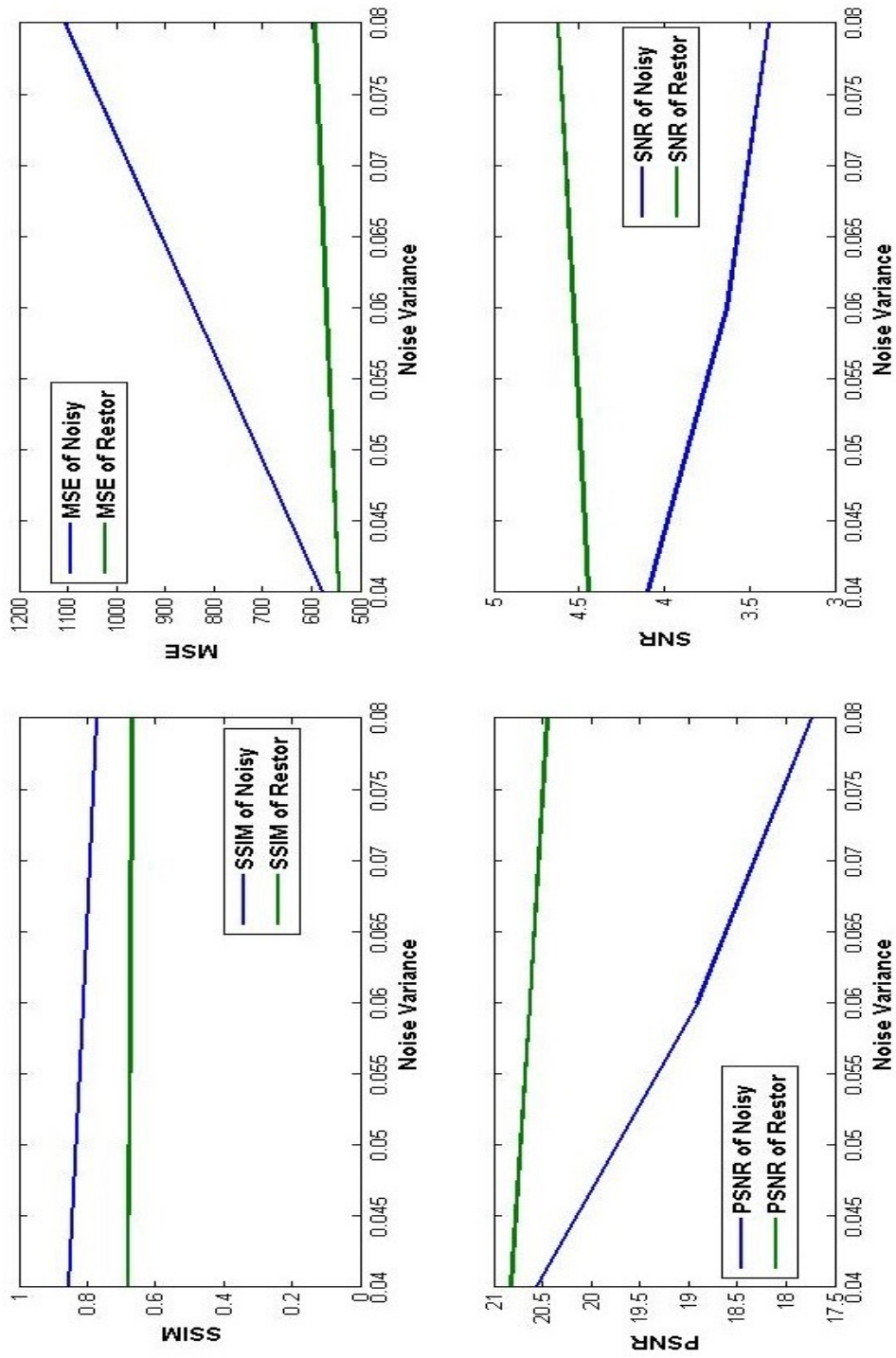


Figure 6.8: Statistical parameters Vs noise variance of sparse domain using hard-thresholding

Experimental Results of Denoising Image in Sparse/Transform Domain with Logarithm

Denoised Standard Image(Lena) in Sparse/Transform Domain with Different Noise Variance using Hard-thresholding with Logarithm



Figure 6.9: (a) Original image, 256 by 256, 8bits/pixel,with $MSE = 0$, $PSNR = \infty$, (b) Restored image of noise var. 0.04, (c) Restored image of noise var. 0.06, (d) Restored image of noise var. 0.08

Denoised Satellite Imagery(SAR) in Sparse/Transform Domain with Different Noise Variance using Hard-thresholding with Logarithm

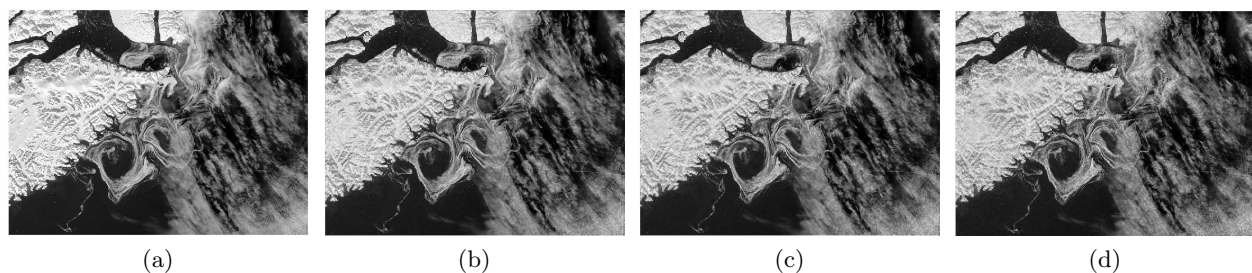


Figure 6.10: (a) Original image, 600 by 800, 8bits/pixel,with $MSE = 0$, $PSNR = \infty$, (b) Restored image of noise var. 0.04, (c) Restored image of noise var. 0.06, (d) Restored image of noise var. 0.08

Result of Hard-Thresholding with Logarithm For Standard Image(Lena)

Table 6.5: Comparison between original, noisy and restored image of Sparse/Transform domain using Hard-thresholding and logarithm function; with different noise variance

Noise Variance	Statistical Parameter Indices	<i>OriginalImage</i> <i>Vs</i> <i>NoisyImage</i>	<i>OriginalImage</i> <i>Vs</i> <i>RestorImage</i>
0.04	SSIM	0.6082	0.8868
	MSE	687.8208	75.9799
	SNR	3.1938	10.7647
	PSNR	19.7900	29.3578
0.06	SSIM	0.5440	0.8660
	MSE	1013.4	111.2189
	SNR	2.7654	10.9372
	PSNR	18.1069	27.7030
0.08	SSIM	0.5015	0.8417
	MSE	1327.4	155.7584
	SNR	2.5371	11.0711
	PSNR	16.9347	26.2403

Result of Hard-Thresholding with Logarithm For Satellite Imagery(SAR)

Table 6.6: Comparison between original, noisy and restored image of Sparse/Transform domain using Hard-thresholding and logarithm function; with different noise variance

Noise Variance	Statistical Parameters Indices	<i>OriginalImage</i> <i>Vs</i> <i>NoisyImage</i>	<i>OriginalImage</i> <i>Vs</i> <i>RestorImage</i>
0.04	SSIM	0.8557	0.8637
	MSE	573.6331	335.9561
	SNR	3.5445	4.4489
	PSNR	20.5785	23.9020
0.06	SSIM	0.8111	0.8511
	MSE	839.5793	410.261
	SNR	3.6298	4.2039
	PSNR	18.9242	22.0342
0.08	SSIM	0.7732	0.8207
	MSE	1100.43	415.785
	SNR	2.9457	3.294
	PSNR	17.7492	21.1914

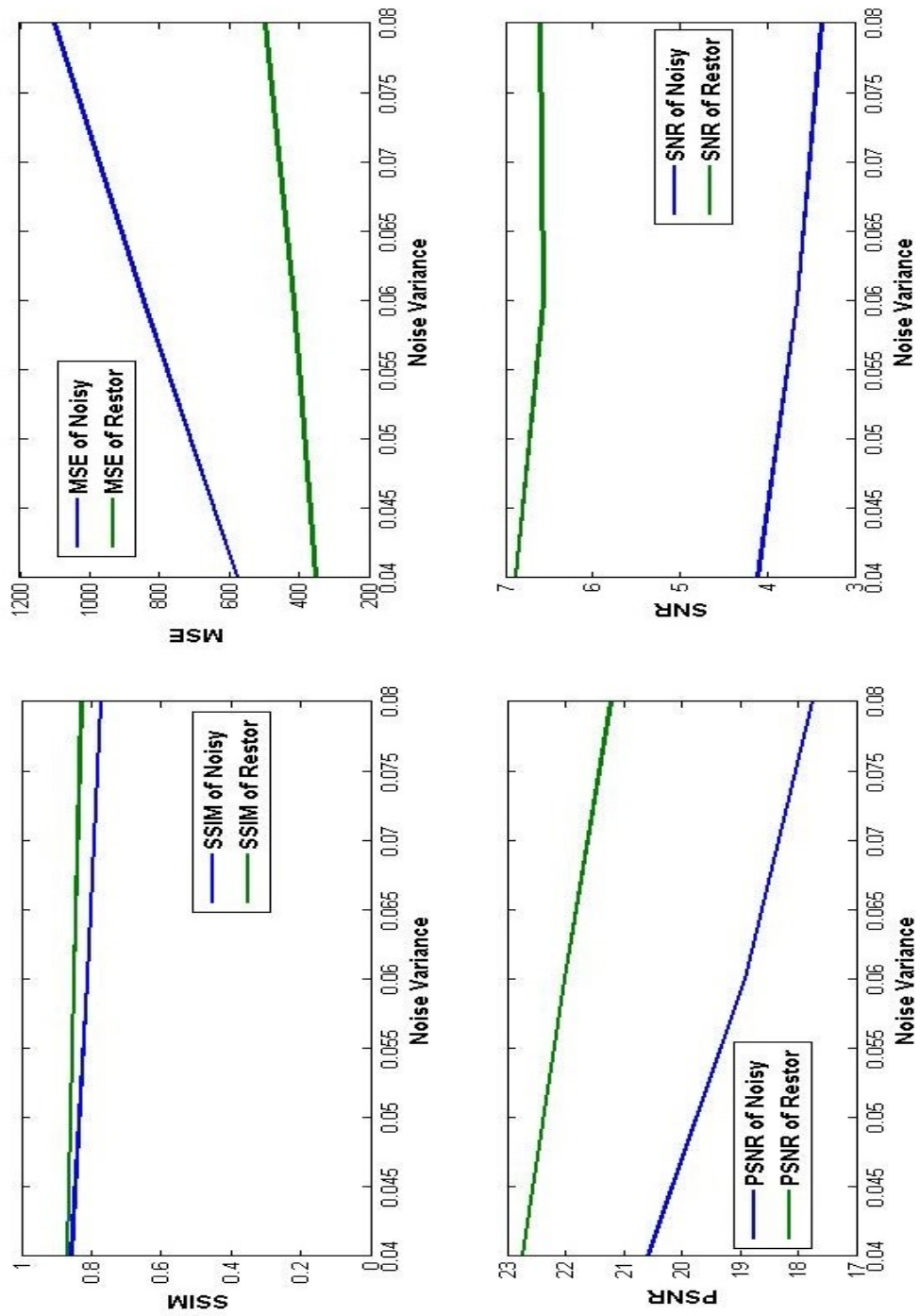


Figure 6.11: Statistical parameters Vs noise variance of sparse domain using hard-thresholding with logarithm

Denoised Bi-modal Image in Sparse/Transform Domain using MCET-thresholding

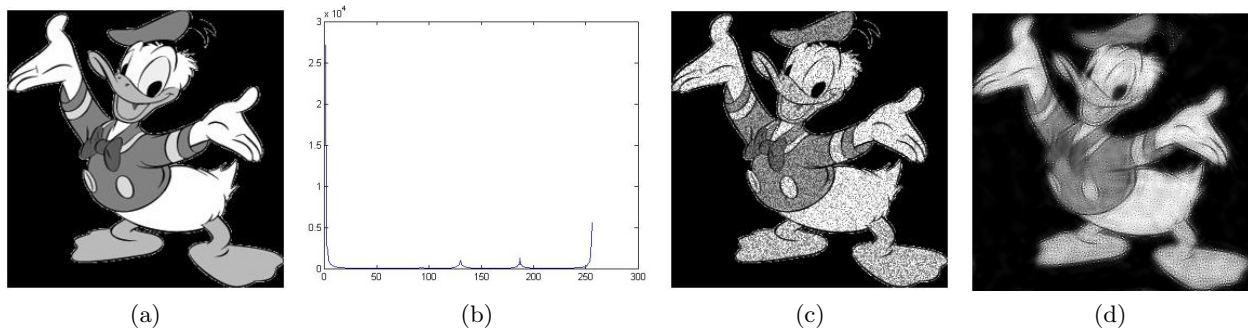


Figure 6.12: (a) Original image, 256 by 256, 8bits/pixel, with $MSE = 0$, $PSNR = \infty$, (b) Restored image of noise var. 0.04, (c) Restored image of noise var. 0.06, (d) Restored image of noise var. 0.08

For Bi-modal Image

Table 6.7: Comparison between original, noisy and restored image of Sparse/Transform domain using MCET-thresholding

Noise Variance	Statistical Parameter Indices	<i>OriginalImage</i> Vs <i>NoisyImage</i>	<i>OriginalImage</i> Vs <i>RestorImage</i>
0.08	SSIM	0.5490	0.7461
	MSE	866.5108	813.6410
	SNR	3.2218	3.8457
	PSNR	18.7871	19.0605

6.2 Chapter Summary

In this chapter, the results of all restoration techniques such as the non-linear Wiener filtering method in Frequency domain, Hard-thresholding in Sparse domain without logarithm and Hard-thresholding in sparse domain with logarithm have been described. The obtained restored image is compared with original image using some quantifying statistical parameters such as SSIM, MSE, SNR, PSNR to measure the performance index. So we conclude that the restoration method Hard-thresholding in Sparse domain using logarithm is better than other nonlinear Wiener filtering in Frequency domain and Hard-thresholding in sparse domain without logarithm methods. The resulted denoised image using hard thresholding in Curvelet domain with logarithm function provides 80% of performance measuring index (SSIM=0.8) with noise variance 0.08. Where, SSIM varies in between 0 to 1. SSIM 0 indicate noisy image and 1 indicate noise free image. So, for getting SSIM close to 1, applying entropy-based thresholding methods in sparse domain and observed that this restoration technique works on only bi-modal images but not getting promising result of statistical parameters and quality performance measuring index. The results of this thesis may show important directions for further scope of research. The conclusion and further scope of research of this work have been described in Chapter: 7.

Chapter 7

CONCLUSION AND FUTURE SCOPE

In this thesis an attempt has been made to develop denoising methods for images under multiplicative noise. The performance of this method is evaluated and compared with that of existing state-of-the-art. In the first section of this chapter an overview of contributions of the thesis and the conclusions are summarized. Topics for future research are pointed out in the second section of this chapter.

7.1 Conclusion

The multiplicative noise are often found to model the real time noise in several images like SAR, Ultrasound image etc. This thesis aims at developing a denoising method under multiplicative noise corruption. A Curvelet domain based approach with different thresholding technique has been developed. The thresholding on Curvelet coefficient is determine by an hard and entropy based thresholding method developed in [8]. The algorithm is applied to several standard images and performance is evaluated using statistical indices like SSIM, MSE, SNR, PSNR. Experimental results exhibits improvement over the exiting stat-of-art for denoising such as Wiener filtering.

7.2 Future Scope

The current research work indicates the ability of the proposed denoising method. However, further investigations may improved the recovered images under multiplicative noise condition. During the research work a few directions for further research have been identified. These are stated below:

- Exploring various thresholding technique in sparse domain.
- Developing restoration technique in real-time embedded platform.

Bibliography

- [1] S. Kumar, P. Kumar, M. Gupta, and A. Nagawat, "Performance comparison of median and wiener filter in image de-noising," *International Journal of Computer Applications (0975-8887) Volume*, 2010.
- [2] E. Candes, L. Demanet, D. Donoho, and L. Ying, "Fast discrete curvelet transforms," *Multiscale Modeling & Simulation*, vol. 5, no. 3, pp. 861–899, 2006.
- [3] J. Starck, E. Candès, and D. Donoho, "The curvelet transform for image denoising," *Image Processing, IEEE Transactions on*, vol. 11, no. 6, pp. 670–684, 2002.
- [4] N. R. Pal, "On minimum cross-entropy thresholding," *Pattern Recognition*, vol. 29, no. 4, pp. 575–580, 1996.
- [5] A. Al-Ajlan and A. El-Zaart, "Image segmentation using minimum cross-entropy thresholding," in *Systems, Man and Cybernetics, 2009. SMC 2009. IEEE International Conference on*. IEEE, 2009, pp. 1776–1781.
- [6] G. Al-Osaimi and A. El-Zaart, "Minimum cross entropy thresholding for sar images," in *Information and Communication Technologies: From Theory to Applications, 2008. ICTTA 2008. 3rd International Conference on*. IEEE, 2008, pp. 1–6.
- [7] E. Cands, L. Demanet, D. Donoho, and L. Ying, "Fast discrete curvelet transforms," 2005.
- [8] M. Sezgin *et al.*, "Survey over image thresholding techniques and quantitative performance evaluation," *Journal of Electronic imaging*, vol. 13, no. 1, pp. 146–168, 2004.
- [9] J. Kittler and J. Illingworth, "Minimum error thresholding," *Pattern recognition*, vol. 19, no. 1, pp. 41–47, 1986.
- [10] J. Kapur, P. K. Sahoo, and A. Wong, "A new method for gray-level picture thresholding using the entropy of the histogram," *Computer vision, graphics, and image processing*, vol. 29, no. 3, pp. 273–285, 1985.
- [11] C. Li and P. Tam, "An iterative algorithm for minimum cross entropy thresholding," *Pattern Recognition Letters*, vol. 19, no. 8, pp. 771–776, 1998.
- [12] J. Sauvola and M. Pietikäinen, "Adaptive document image binarization," *Pattern Recognition*, vol. 33, no. 2, pp. 225–236, 2000.
- [13] M. Sezgin and R. Taşaltın, "A new dichotomization technique to multilevel thresholding devoted to inspection applications," *Pattern Recognition Letters*, vol. 21, no. 2, pp. 151–161, 2000.

- [14] J.-S. Chang, H.-Y. M. Liao, M.-K. Hor, J.-W. Hsieh, and M.-Y. Chern, "New automatic multi-level thresholding technique for segmentation of thermal images," *Image and vision computing*, vol. 15, no. 1, pp. 23–34, 1997.
- [15] D.-M. Tsai, "A fast thresholding selection procedure for multimodal and unimodal histograms," *Pattern Recognition Letters*, vol. 16, no. 6, pp. 653–666, 1995.
- [16] J.-C. Yen, F.-J. Chang, and S. Chang, "A new criterion for automatic multilevel thresholding," *Image Processing, IEEE Transactions on*, vol. 4, no. 3, pp. 370–378, 1995.
- [17] L. Hertz and R. W. Schafer, "Multilevel thresholding using edge matching," *Computer Vision, Graphics, and Image Processing*, vol. 44, no. 3, pp. 279–295, 1988.
- [18] L. OGorman, "Binarization and multithresholding of document images using connectivity," *CVGIP: Graphical Models and Image Processing*, vol. 56, no. 6, pp. 494–506, 1994.
- [19] N. Papamarkos and B. Gatos, "A new approach for multilevel threshold selection," *CVGIP: Graphical Model and Image Processing*, vol. 56, no. 5, pp. 357–370, 1994.
- [20] G. Subrahmanyam, A. Rajagopalan, and R. Aravind, "A recursive filter for despeckling sar images," *Image Processing, IEEE Transactions on*, vol. 17, no. 10, pp. 1969–1974, 2008.
- [21] J. Bruniquel and A. Lopes, "Multi-variate optimal speckle reduction in sar imagery," *International journal of remote sensing*, vol. 18, no. 3, pp. 603–627, 1997.
- [22] J.-S. Lee, L. Jurkevich, P. Dewaele, P. Wambacq, and A. Oosterlinck, "Speckle filtering of synthetic aperture radar images: A review," *Remote Sensing Reviews*, vol. 8, no. 4, pp. 313–340, 1994.
- [23] S. Sudha, G. Suresh, and R. Sukanesh, "Speckle noise reduction in ultrasound images by wavelet thresholding based on weighted variance," *International journal of computer theory and engineering*, vol. 1, no. 1, pp. 1793–8201, 2009.
- [24] K. Thangavel, R. Manavalan, and I. L. Aroquiaraj, "Removal of speckle noise from ultrasound medical image based on special filters: comparative study," *ICGST-GVIP Journal*, vol. 9, no. 3, pp. 25–32, 2009.
- [25] I. LJB Development, "Speckle Reduction in Ultrasound Imaging," <http://www.ljbdev.com/speckle.html>.
- [26] K. Z. Abd-Elmoniem, Y. M. Kadah, and A. Youssef, "Real time adaptive ultrasound speckle reduction and coherence enhancement," in *Image Processing, 2000. Proceedings. 2000 International Conference on*, vol. 1. IEEE, 2000, pp. 172–175.
- [27] K. Z. Abd-Elmoniem, A. Youssef, and Y. M. Kadah, "Real-time speckle reduction and coherence enhancement in ultrasound imaging via nonlinear anisotropic diffusion," *Biomedical Engineering, IEEE Transactions on*, vol. 49, no. 9, pp. 997–1014, 2002.
- [28] C. H. Li and C. Lee, "Minimum cross entropy thresholding," *Pattern Recognition*, vol. 26, no. 4, pp. 617–625, 1993.
- [29] A. Ali, P. Swami, and J. Singhai, "Modified curvelet thresholding algorithm for image denoising," *Journal of Computer Science*, vol. 6, no. 1, pp. 18–23, 2010.

- [30] T. Pun, "Entropic thresholding, a new approach," *Computer Graphics and Image Processing*, vol. 16, no. 3, pp. 210–239, 1981.
- [31] N. R. Pal and S. K. Pal, "Entropic thresholding," *Signal processing*, vol. 16, no. 2, pp. 97–108, 1989.
- [32] A. Brink, "Thresholding of digital images using two-dimensional entropies," *Pattern recognition*, vol. 25, no. 8, pp. 803–808, 1992.
- [33] A. S. Abutaleb, "Automatic thresholding of gray-level pictures using two-dimensional entropy," *Computer Vision, Graphics, and Image Processing*, vol. 47, no. 1, pp. 22–32, 1989.
- [34] Z. Wang, A. C. Bovik, H. R. Sheikh, and E. P. Simoncelli, "Image quality assessment: From error visibility to structural similarity," *Image Processing, IEEE Transactions on*, vol. 13, no. 4, pp. 600–612, 2004.
- [35] Z. Wang and A. C. Bovik, "Modern image quality assessment," *Synthesis Lectures on Image, Video, and Multimedia Processing*, vol. 2, no. 1, pp. 1–156, 2006.
- [36] A. Horé and D. Ziou, "Image quality metrics: Psnr vs. ssim," in *Pattern Recognition (ICPR), 2010 20th International Conference on*. IEEE, 2010, pp. 2366–2369.
- [37] Z. Wang and A. C. Bovik, "A universal image quality index," *Signal Processing Letters, IEEE*, vol. 9, no. 3, pp. 81–84, 2002.

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