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Sliced Redgelet Transform For Image Denoising

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SLICED RIDGELET TRANSFORM FOR IMAGE DENOISING

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DECLARATION BY THE CANDIDATE

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I, hereby, declare that the work presented in this thesis, entitled " **SLICED RIDGELET TRANSFORM FOR IMAGE DENOISING**" in fulfillment of the requirements for the award of Degree of Doctor of Philosophy of Mewar University, Chittorgarh, Rajasthan is an authentic record of my own research work carried out under the supervision of **Dr. G. Manoj Someswar**. I, also declare that the work embodied in the present thesis is my original work and has not been submitted by me for any other Degree or Diploma in any University/Institution.

Date: 31/01/2016 Signature of the Research Scholar

Place: Mewar University VANKDOTH KRISHNANAIK

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Supervisor Name: Dr. G.Manoj Someswar

Supervisor Designation: Professor

Date: 31: 1:2016

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VANKDOTH KRISHNANAIK

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ABSTRACT

Image Quality becomes an essential aspect for various image and video processing based applications. Quality of captured images are often does not meet the expected quality scale due to noisy in images. Image noisy ratio effects on image processing and image relevant decision making applications, and cause to inaccurate and erroneous results. Image Noisy removing (Image De-noising) is the first and foremost requirement for any image and video processing applications. Although some previous researches were introduced various new approaches on this area, still this area is suffering from accuracy, quality and reliability. Henceforth, this thesis concentrates on implementing an accurate and scalable image de-noising approach to achieve the high quality, which helps better than existed technologies of image or video processing.

Recent trends in ridgelet transforms proven that they are better than wavelet transforms to reduce the noise in images. This thesis concentrates on improvising the features of ridgelet transform to perform well than what it stands. As per our concern there is a wide research area and scope is still waiting for research concentration in ridigelet transforms.

Although several de-noising techniques were introduce by previous research scholars, Image processing is still suffering from the noise problem and results accuracy is affecting due to the blur or noise data of an image. Various image noise problems were existed in processing standard, orthogonal and limited size images are: additive white noise, Thermal noise, Fixed Pattern noise, Quantization noise, Dark current

noise etc. Popular de-noising techniques were proposed in the area of image processing recently like wavelets, curvlets and some other edge based technologies, they have problem with complexity in finding approximate shift invariant property of the dual-tree and high directional sensitivity etc.

In order to overcome the above mentioned problems we are designing and implementing an integrated, comprehensive and scalable solution is sliced ridgelet transformation for image de-noising. This Research work introduces sliced ridgelet transform for image de-noising, and to achieve the scalability and accuracy and in a reliable manner of image processing. Image de-noising that is based on ridgelets computed in a localized manner and that is computationally less intensive than curvelets, but similar donoising performance. Sliced ridgelet transform's ridge function is segregated to multiple slices with constant length. Single-dimension wavelet transforms are used to compute the angle values of each slice in sliced ridgelet transform. Ridgelet co-efficient are obtained for the base threshold calculation to implement the accurate de-noising.

This research work compares the accuracy and scalability of image de-noising with other popular approaches like wavelets, curvlets and some other inter-relevant technologies. Experimental results are proving that the sliced ridgelet approach is having the better performance than the other popular techniques.

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CHAPTER -1

INTRODUCTION

Objectives of this chapter

1.1 Introduction

In this era of internet, usage of image is increased day by day in different areas such as fashion, art, design, animation, advertising and finger print identification. Image processing is very important and base technology for many real time applications like image search engines, image clustering, image segmentation, Entropy detection etc. Image clarity (clear pixel resolution) is an important property of image and maximum percentage is expected for image processing applications. This is one of the factors to determine the accuracy of image processing results. The increased level of clarity will increase the result accuracy dramatically and also makes the results reliable.

Image blurriness is the common problem in the area of image processing, which is also called as noisy of image. This problem should be resolved before image processing to alleviate the burden and bottlenecks of image processing. Comparison, segmentation and clustering of an image are expecting the clear removal of noisiness in the given image is called as Image De-noising.

Image de-noising is one of the most popular research fields in image processing due to fact that it is extremely difficult to form a general global de-noising scheme effective for all types of noise as well as all type images. A common problem in image de-noising is the blurring of the prominent edges in the image which can cause discrepancies when the de-noising operation is combined with other operations such as image edge detection and segmentation.

The recent proposed procedures by various authors has been introduced image de-noising based on transforms such as wavelets, curvelets, exploit redundancy and threshold to remove the noise without blurring the edges. Although many previous approaches have been introduced in this area so far, none of them are resolved the image noising issue up to the expected level of image processing. Although wavelet transform is the better existing technology than others it is also suffering from some transformation problems like Shift sensitivity, Poor Directionality and Absence of Phase information. In recent ridgelet transforms proven that, they are better than wavelet transforms [1] to implement the de-noising procedure for images in image processing applications.

In this research, we introduced "Sliced Ridgelet Transform for Image De-noising" to mitigate the burden of image de-noising process and to improvise the image display resolution depth (image clarity) to extract the best results while working with image processing applications. This scheme also addresses the main issues and disadvantages of wavelet transform like Shift sensitivity, Poor Directionality and Absence of Phase information while doing the image de-noising process. The important characteristic of the de-noising technique introduced in this project is that it can reduce considerably the noise without destroying the edges of the objects in the image.

Experimental results with MATLAB software is proving our thesis scalability, accuracy and reliability while comparing with other schemas like wavelet transform and curvelet transform. These results were stated that, usage of sliced ridgelet transform model is having the better performance than other transform schemas.

1.2 Problem Statement

Recently the image and video utilization is increased dramatically in various applications and exactly image processing applications become an integral of human life. From simple image transform apps in mobile to CCTV recorded video feature extraction; image processing is working at background. Due to the noise in images, the results of image processing may not accurate and reliable up to the threshold level.

Several research articles have been worked on this problem of image de-noising but they are suffering from various problems at each approach level. If we consider the popular technology wavelet transform for image de-noising is having the limitations are Shift sensitivity, Poor Directionality and Absence of Phase information. Similarly another popular technique curvlets also suffering from various problems like loss of sensitivity [2], amplifying the noise (linearly) as well as the signal of interest [3]. These problems are effecting on image de-noising process results in terms of accuracy and scalability. We explored these problems in detail, at this thesis related work.

To overcome the above problems in my thesis introduced the “Sliced Ridgelet Transform for Image De-noising” to mitigate the complexity of image de-noising process and to improvise the image display resolution depth (image clarity) to extract the best results while working with image processing applications. This scheme also addresses the main issues and disadvantages of wavelet transform like Shift sensitivity, Poor Directionality and Absence of Phase information while doing the image de-noising process. The important characteristic of the de-noising technique introduced in this project is that it can reduce considerably the noise without destroying the edges of the objects in the image.

1.3 Motivation and Need of Research Topic

In general, noise gives an image with undesirable appearance, the most significant factor is that noise can cover and reduce the visibility of certain features within the image, which may play vital role in understanding the whole meaning of image or helpful in processing the image feature extraction. The loss of visibility is especially significant for low-contrast images like medical image, scanned images and X-ray images.

There are several facts and factors motivated me to do this research in a dissimilar way to find a better solution perform image de-noising are:

- Image de-noising is very important for several image processing schemas.
- Image de-noising plays a vital role in medical disease symptom identification, severity and root causes.
- Image de-noising is a prominent pre-processing technique in video processing (feature extraction, frames creation and background removal process)

As this is a backbone process for many real time applications, our thesis concentrated on this area (image de-noising) and dedicated to improvise the performance of this in a reliable and accurate way.

Regardless of which digital camera we are using and how much light is focusing on object (to improvise the quality), the major limitations of image processing are blur and noise. These are several methods were proposed to eliminate blur from images and sometimes the blur will be considered as another type of noise data only. The second important issue is noise of digital images.

Noise of an image will always shows impact on image processing results, because the increased noise ratio in image processing will reduce the quality of image and also makes the images processing results not reliable. Like similarly, decreased ratio of image noise will make the image as perfect in terms of quality, which makes the image processing results reliable.

Because of the above specified reasons we need to concern on this research area to remove the noise from image using sliced ridgelet image transform for better results.

1.4 Sliced Ridgelet Transform for Image De-noising

Image de-noising is the back bone of image processing and its dependent applications. Most popular technologies of image de-noising are wavelet transform, curvelet transform and ridigelet transform. Ridigelet transform [4 and 5] was introduced to avoid the potential bottleneck problems of image processing are inevitability and non-redundancy. These problems were effecting on performance of image processing dramatically and caused to unexpected results and result invariants.

Recently ridgelet transform become an alternative to overcome the problems in image processing with wavelets transform. The 2D wavelet transform of images produces large wavelet coefficients at every scale of the decomposition. With so many large coefficients, the de-noising of noisy images faces a lot of difficulties. This is become a big problem in processing of images with an efficient legacy wavelet mechanism. Ridgelet transform was successfully applied on digital image processing with different orientations and locations. Unlike wavelet transforms [6 and 7], the ridgelet transform processes data by first computing integrals over different orientations and locations. A ridgelet is constant along the lines $x1 \cos \beta + x2 \sin \beta = \text{constant}$. In the direction orthogonal to these ridges it is a wavelet. Ridgelets have been successfully applied in image de-noising recently.

Ridgelets is a novel feature in image processing, which applied in the research area of image de-noising. For each a>0, each $b \in R$ and each $\Theta \in [0,2\pi)$, the bipartite ridgelet $(_\pi\, a,b)$,: $R^2 \rightarrow R$ is defined as

$$ƛ\,(a, b, _\Theta) = a^{(-1/2)}\, ƛ\,((x1 \cos \Theta + x2 \sin \Theta - b)/a),$$

Where ƛ is a predefined wavelet method. Ridgelet value is static with the lines

$$ƛ\,(x1 \cos x) + ƛ\,(x2 \sin y) = \text{static constant.}$$

Diagonal to these ridgesit is a well formed wavelet. Given an in variant bipartite image f(x1,x2), and we can write its ridgelet (for each (p>0) and ($q \in R$)) significant formula as:

$$R\,(p, q, \Theta) = p, q, \Theta, f[(ƛ)\,(x1,x2)\, d(x1)\, d(x2)].$$

The given below figure 1.A shows the basic ridgelet function with its sliced transforms.

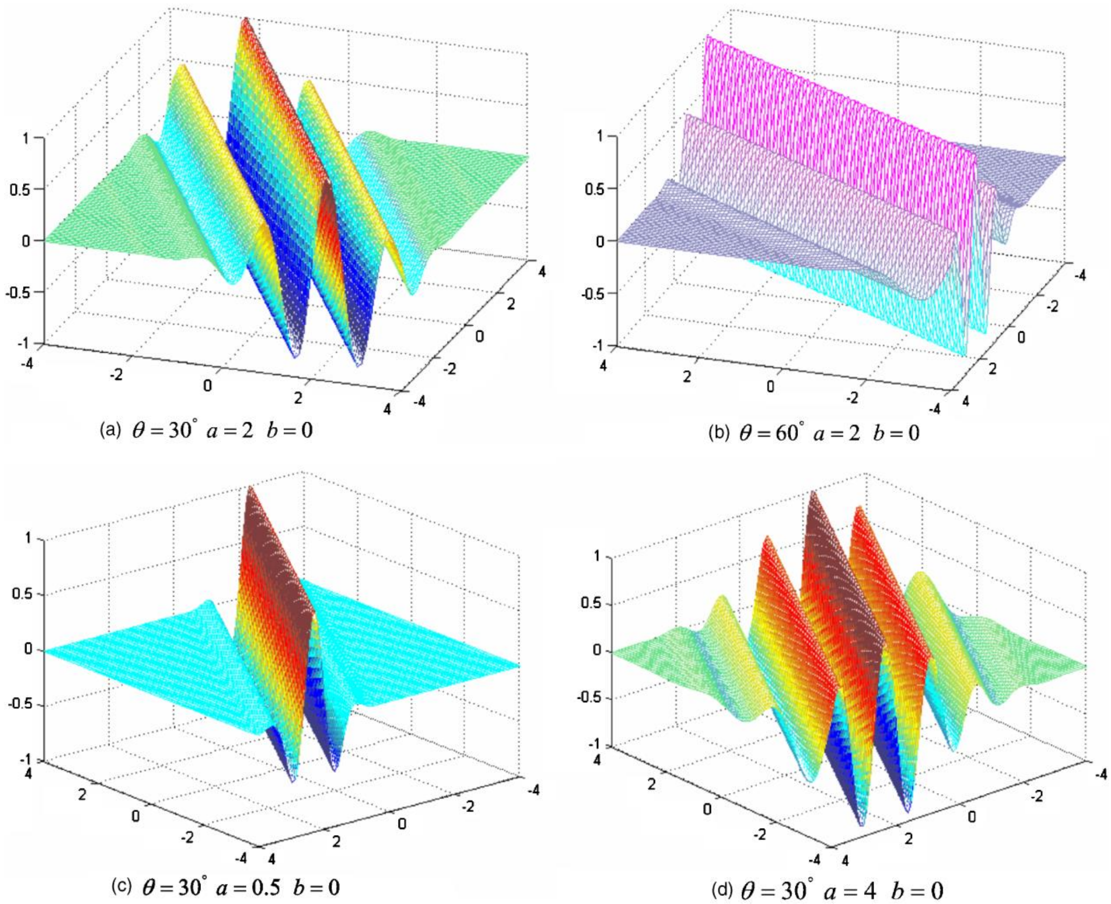

Fig 1.A Basic Sliced ridgelets formation with various angular variable θ values

The above diagram specifies the various constant θ values and their respective ridgelets curved area of an image. By varying the values of a and θ we just shown the image representations. As per the requirement these ridgelets might be scaled , shifted and rotated also.

Sliced ridgelet transform is a multi-dimensional and precise wavelet transform with slices. In this approach the θ is a random static constant and the value will be change frequently. Ridgelets are quite varied from wavelets in the view of ridgelets parade very high directional sensitivity and are highly anisotropic. This high anisotropic value is caused to get the best results while implementing the image de-noising techniques. An exceeded ridgelet transform can be performed in the Fourier domain. Initially for the given image the 2D FFT [8 and 9] is computed. Interpolation process will continue with along a number of straight lines equal to the selected number of projections. Each line passes through the center of the 2D frequency space, with a slope equal to the projection angle, and the number of interpolation points equal to the number of rays per projection. After the 1D inverse FFT along each interpolated ray, we perform a 1D wavelet transform.

1.5 Aims and Objectives

Image processing is still suffering from the noise problem and results accuracy is affecting due to this blur or noise data of an image. Several image noise problems were existed in processing standard, orthogonal and limited size images are: additive white noise, Thermal noise, Fixed Pattern noise, Quantization noise, Dark current noise etc. Although various de-noising techniques were proposed in the area of image processing like wavelets, curvlets and some other edge based technologies, they have problem with complexity in finding approximate shift invariant property of the dual-tree and high directional sensitivity etc. In order to overcome the above mentioned problems we are designing and implementing an integrated, comprehensive and scalable solution is sliced ridgelet transformation for image de-noising.

The main aim and contributions of this research work are:

- Exploring the concept of image de-noising
- Discussion about various image noising types
- Closure look at the existed transforming techniques
- Finding the best possible solutions for several image noise problems
- Extending the ridgelet technology to implement sliced ridgelet transform
- Reducing the directional sensitivity and resisting from absence of phase information
- Designing the feasible way to find approximate shift invariant property
- Comparison of sliced ridgelet results with other popular techniques

1.6 Overview of Original Contributions

Original contributions of this thesis are concentrating on towards achieving the aims of this research work. My research thoroughly studied the various implementations in the area of image processing and image de-noising to get a rigid overview, which helps to continue my research journey.

My research contributions allowed me to achieve this challenging task with expected results. Although several contributions were made for this project from my side, there some noticeable contributions are:

We designed sliced ridgelet transform technique to overcome the limitations of popular transformation approaches like wavelet transform and curvlets transform [10].

We introduced the respective best sliced ridgelet solutions for noise problems in image processing (image de-noising).

As we mentioned in the above section (aims and objectives) we reduced the directional sensitivity and dependency invariants of image de-noising with sliced ridgelets.

My research compares the accuracy and scalability of image de-noising with other popular approaches like wavelets, curvlets and some other inter-relevant technologies.

We strongly believe that the above contributions not only meet my research goal, and also improvise the image de-noising accuracy and scalability.

1.7 Research Methodology

This thesis has been applied with the quantitative based approach as research methodology. My Research has selected this method, because as the name suggests, this is concerned with trying to quantify things; it asks questions such as ‘how long’, ‘how many’ or ‘the degree to which’. Quantitative methods look to quantify data and generalize results from a sample of the population of interest. They may look to measure the incidence of various views and opinions in a chosen sample for example or aggregate results.

The quantitative methodology applied to this thesis has been framed as described below.

Initially this research do the analysis over existing image de-noising approaches would be defined as Literature Review on image de-noising. This analysis outlines the problems and limitations with every image de-noising methodology treated as Problem Definition. This leads to identify the main aim of the research as a collection of Research Objectives. Designing the solutions for identified problems and limitations should be followed by the feasible study as Research Design. Implementing the possible solutions to address the research problems to achieve the aim is the next stage in this methodology. Comparison of current thesis results with previous researches would be considered as Result Comparison. The final part of the method is used in the thesis is the conclusion that carries out the contribution and future expectations of this thesis.

1.8 Thesis Outline

This thesis is structured into 6 chapters. Chapter 1 gives the introduction to the thesis; chapter 2 concentrates on literature review and Problem Definition with various image de-noising methods. Chapter 3 presents the introduction and implementation of sliced ridgelet transform. Chapter 4 describes the Literature review of sliced ridgelet transform approach and chapter 5 implements the experiments on metamorphic testing and its relevant methodologies with result comparison metamorphic relations for testing Graph Theory Algorithms. Chapter 6 concludes the research work along with future expectations. Appendix-A discuss about MATLAB Software and Appendix-B provides the sample MATLAB code functions.

CHAPTER -2

RELATED WORK

Objectives of this chapter

2.1 Introduction

2.2 Related work

2.3 What is Digital Image?

2.4 Digital Image Properties for Processing

- *Pixel Distance*
- *Pixel Adjacency*
- *Vector and lines*
- *Border*
- *Edge*
- *Edge Direction*
- *Crack Edges*
- *Brightness*

2.5 What is Noise in Image?

- *ISO*
- *Sensor Size*
- *Pixel Density*
- *Exposure Time*
- *Shadows*

2.6 Types of Noise in Images

- *Photo electronic noise*
- *Impulse Noise*
- *Structured Noise*
- *Amplifier noise*
- *Shot Noise*
- *Quantization noise*
- *Speckle Noise*

2.7 Phases of Digital Image Processing

- *Digital Image Processing*
- *Adv of Digital Image Processing*
- *Image Processing Applications*
- *Phases of Image Processing*
- *Block Diagram of Image processing with basic steps*
    - *Image Acquisition*
    - *Image Enhancement*
    - *Image Restoration*
    - *Color Image Processing*
    - *Wavelets and Multi resolution Processing*
    - *Compression*
    - *Segmentation*
    - *Representation and Description*
    - *Object Recognition*
    - *Knowledge Base*

2.8 Image De-noising Methods

- *What is image De-noising?*
- *Need of Image De-Noising*
- *History of Image De-noising*
- *Image De-noising Methods*
  - *Spatial dependent De-noising*
    - *Non-Linear Filters*
    - *Linear Filters*
  - *Transform based De-Noising*
    - *Non-Adaptive transform*
    - *Adaptive Transform*

2.9 Summary

"***We strongly believe that, Related Work and Literature Review are the backbone for the entire research work***"

2.1 Introduction

As part of this project analysis, a distinct related work and literature review was conducted at the beginning of this research work. Apart from that, while introducing the naïve and complex concepts also this research thoroughly reviewed some more valuable references. During the review of research, many up-to-date techniques were revised and arranged as a bottom-top hierarchical manner to understand the research improvement in order. This through knowledge is essentially required while beginning of a new research journey. In our journey we have encountered the need of review some generic and related concepts to build our research work. We described the generic concepts as related work and relevant concepts as literature review in this chapter. We would be always thankful to the authors of these concepts related article references.

This chapter is composed with two main divisions are related work and literature review sections.

In Related Work section we discuss about the comprehensive view of basic image definition, image properties, image noising, Types of image noising, need of image transform, phases of image processing, block diagram with basic steps of image processing, image donoising methods for the current research work. This section covers the important information regarding to each of the above concept in detail.

In Literature review section we explore the knowledge about our thesis scope means sliced ridgelet transform and its empowerment. Apart from that we also discussed about the other relevant concepts of are wavelet transform [11, 12 and 13], curvlet

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transform [14 and 15] and edge based transform methodologies [16 and 17] etc. Apart from this with each technology we explore the advantages and disadvantages. This section covers the entire basics of image donoising methods, sliced ridgelet transform [18, 19 and 20] etc.

We also included the relevant proceedings, journals and publishers information as bibliography at the end of this research work.

2.2 Related work

Like other related works, this work also highlights the related topics of research done by other authors in our research area. This is like accompanying the research knowledge by looking into others research work. All the concepts here we discussed are related to our research context either directly or indirectly.

Here in this research we are committed to thoroughly discuss all image denoising related concept in detail.

2.3 What is Digital Image ?

In general an image is a collection of 2D grid with the collection of pixels and having the properties like height and width, which also measured in pixel. Each pixel is square and has a fixed size on a given display. Different computer monitors may use different sized pixels as per their requirement to display them.

Every pixel is having a specified color. The color value is a 32-bit integer or is equivalent to 4 bytes. If we consider these bits in a sequential manner, the initial eight bits represents the red color density of the pixel, the second eight bits represents the green color density, the third eight bits specifies the blue color density, and the remaining last set of eight bits specifies the transparency value of the pixel as shown in below diagram 2.1.

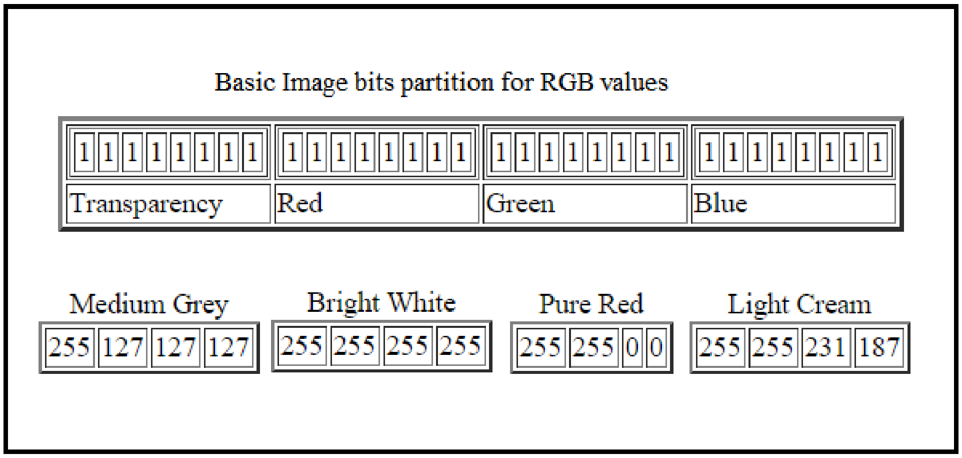


Figure 2.A Basic Image bit classification and representation

Each of these values can be interpreted as an unsigned byte between 0 and 255. Within the color higher numbers are brighter. Thus a red of 0 is no red at all while a red of 255 is a very bright red. Currently modern image processing technologies only supports two levels of transparency: Completely opaque (255) and completely transparent (0). Values of 1 through 254 are treated as completely transparent.

Different colors are made by mixing different levels of the three primary colors as shown in above diagram 2.A. For example, medium gray is 127 red, 127 green, and 127 blue.Pure white is 255 red, 255 green, 255 blue. Pure red is 255 red, 0 green, 0 blue. A light cream is 255 red, 231 green, and 187 blue.

In the area of image processing young and takeda at el [21] assumed the image is as explained below in their image processing fundamentals book.

A digital image a [m, n] described in a 2D discrete space is derived from an analog image a(x, y) in a 2D continuous space through a sampling process that is frequently referred to as digitization.

The 2D continuous image a(x, y) is divided into N rows and M columns. The intersection of a row and a column is termed a pixel. The value assigned to the integer coordinates [m,n] with {m=0,1,2,…,M–1} and {n=0,1,2,…,N–1} is a[m,n]. In fact, in most cases a(x, y) – which we might consider to be the physical signal that impinges on the face of a 2D sensor – is actually a function of many variables including depth (z), color (λ), and time (t).

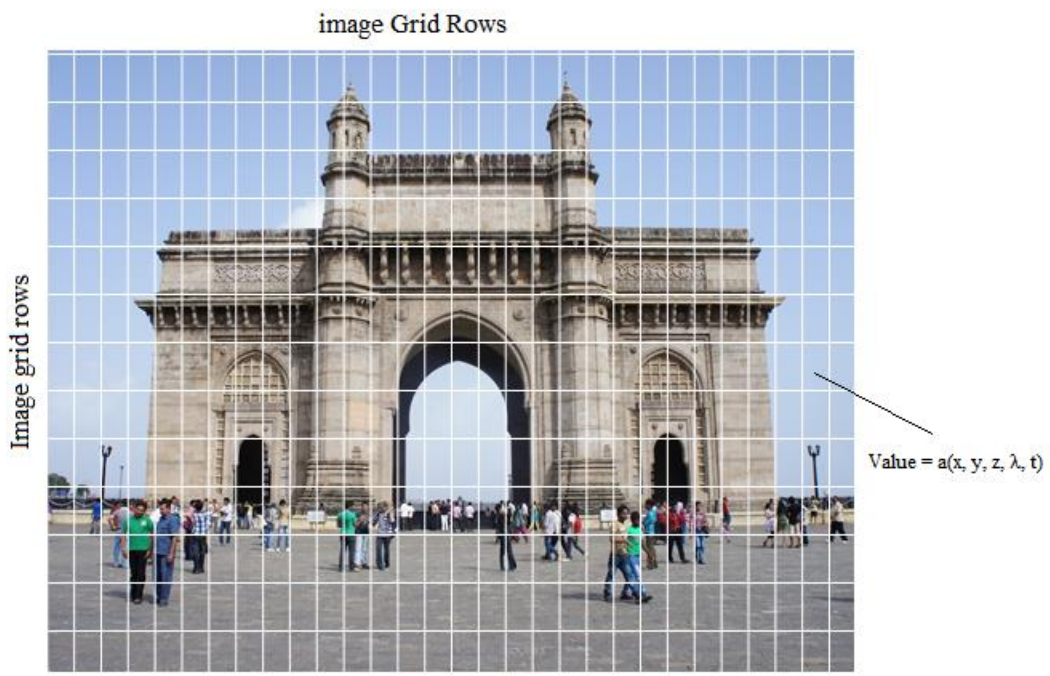


Fig 2.B Basic image with grid representation

The value assigned to every pixel is the average brightness in the pixel rounded to the nearest integer value. The process of representing the amplitude of the 2D signal at a given coordinate as an integer value with L different gray levels is usually referred to as amplitude quantization or simply quantization.

A digital image is typically composed of picture elements (pixels) located at the intersection of each row i and column j in each K bands of imagery. Associated with each pixel is a number known as Digital Number (DN) [22] or Brightness Value (BV) [22], which depicts the average radiance of a relatively small area within a scene showed in below figure 2.C

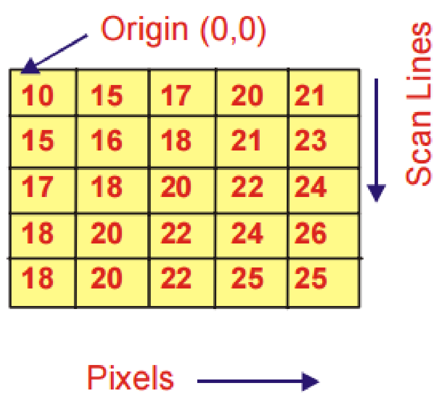


Figure 2.C Origin, Scan lines and Pixels formation of an Image

In above figure 2.C smaller number indicates low average radiance from the area and the high number is an indicator of high radiant properties of the area. The size of this area effects the reproduction of details within the scene. As pixel size is reduced more scene detail is presented in digital representation.

2.4 Digital Image Properties for Processing

Digital images are having the various properties like metric properties and topological for image processing. These properties and their representation is very important while image processing. They also helpful in various image processing software's like MATLAB [23, 24 and 25], DIMG [26] and others. My research considers these properties and listed them in an order with proper explanation.

- Pixel Distance
- Pixel Adjacency
- Vector and lines
- Border
- Edge
- Edge Direction
- Crack Edges
- Brightness

Pixel Distance is a value is the distance between two pixels in a digital image is a significant quantitative measure [27]. Although image is a two-dimensional matrix, the distance between the two pixels is very important while working with image processing.

The distance between points with co-ordinates (i, j) and (h, k) may be defined in several different ways;

Euclidean distance [27] between the two given pixels is defined as:

$$D_E((i,j),(h,k)) = \sqrt{(i-h)^2 + (j-k)^2}$$

City Bock distance [27] between the two given pixels is defined as:

$$D_4((i,j),(h,k)) = | i - h | + | j - k |$$

Chess Board distance [27] between the two given pixels is defined as:

$$D_8((i,j),(h,k)) = max\{| i - h |, | j - k |\}$$

Pixel Adjacency is another important image topological property [28] defined as 4-neighborhood and 8-neighborhood. Let V is the adjacency of a gray scale image and V={1} in case of two neighbor pixels with value 1. In grey scale image format the adjacency value is set to be in 0 to 255.

The 4- neighborhood (adjacency) of an image pixels is with values of V from 4 and the set is $n_4(p)$ as shown in below figure 2.D.

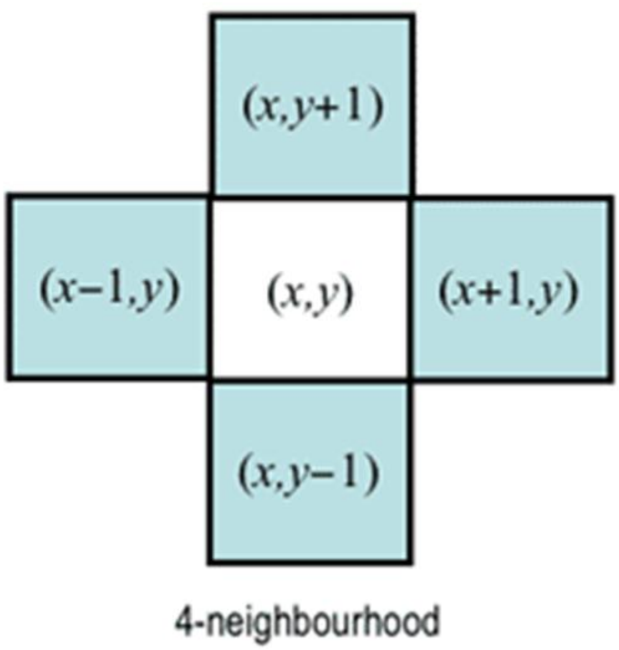


Figure 2.D 4- neighborhood (adjacency) of an image

The 8- neighborhood (adjacency) of an image pixels is with values of V with value 8 and the set is n8 (p) as shown in below figure 2.E.

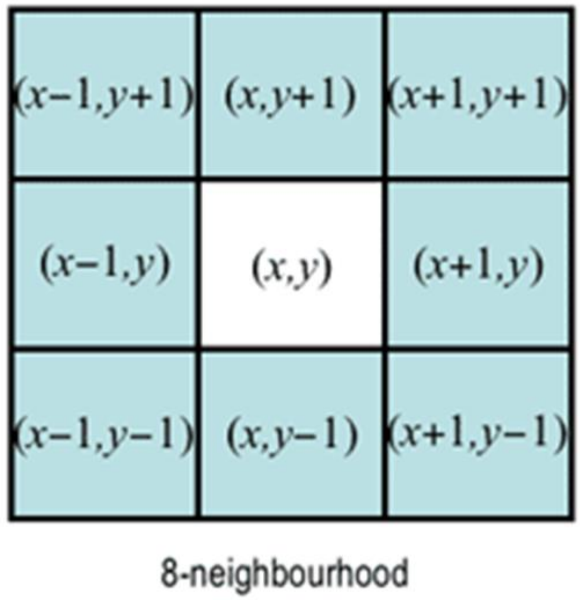


Figure 2.E 8- neighborhood (adjacency) of an image

Vector images have data that describe lines and curves. These images can be enlarged and still maintain their smooth edges (not pixilated like bitmap images). Artists and designers will often work with vector images [28], and then “rasterize” the finalized version for distribution and display. Adobe Illustrator files (.ai) and CorelDraw files (.cdr) are examples of vector images. Figure 2.F represents the lines and curve image properties with image grid (matrix).

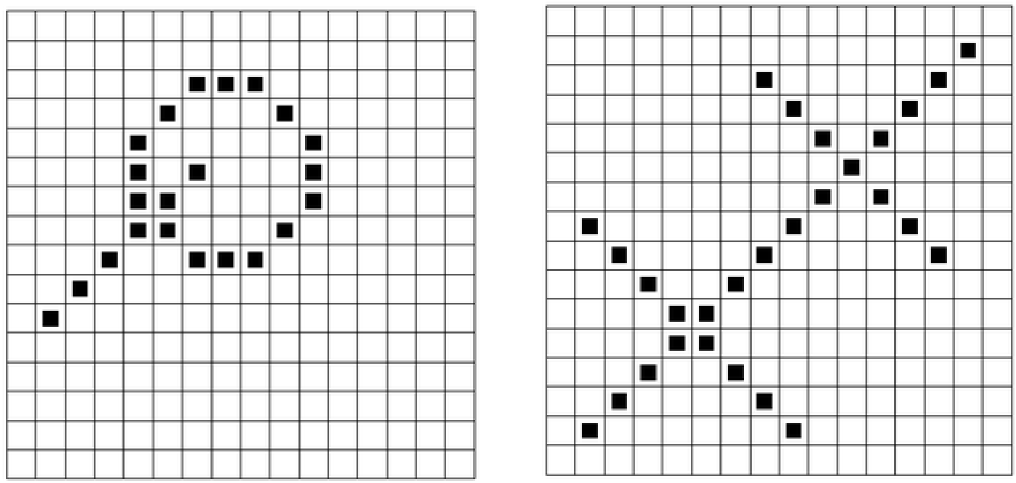


Figure 2.F Image Grid with Curve and vectors (lines)

Border R for a digital image [27 and 28] is a collection of pixels in the given image region with one or more neighborhoods of R. These borders are classified into inner borders and outer borders.

Edge is a local property [27 and 28] of a pixel and its immediate neighborhood. it is a vector given by a magnitude and direction.

Edge Direction is perpendicular to the gradient direction which points in the direction of image function growth.

Cracked Edge: four crack edges [27 and 28] are attached to each pixel, which are defined by its relation to its 4-neighbors. The direction of the crack edge is that of increasing brightness, and is a multiple of 90 degrees, while its magnitude is the absolute difference between the brightness of the relevant pair of pixels.

Brightness An image defined in the "real world" is considered to be a function of two real variables, for example, a(x, y) with a as the amplitude (e.g. brightness) of the image at the real coordinate position (x, y). The value assigned to every pixel is the average brightness in the pixel rounded to the nearest integer value. The process of representing the amplitude of the 2D signal at a given coordinate as an integer value with L different gray levels is usually referred to as amplitude quantization. we can define the probability distribution function of the brightness in that region and the probability density function of the brightness in that region.

2.5 What noise in Image?

The visual distortion of a digital image is called noise [29]. In general this is digital equivalent to grain found in film photographs.

In technical noise is described as a process (P) that degrades the digital image (K) and unwanted part of an image can be defined as:

$$K(i, j) = K(i, j) + P(i, j)$$

This is mainly caused by various reasons like pixel level variations, poor background brightness, high volume sound effects of source (camera) device, natural disasters (rain, winds etc) and technical problems of camera or video device etc.

Depends on the circumstances noise level may vary from one to another. Based on noise percentage and digital data formation, we should select appropriate donoising technique. In majority cases this noisy level will degrades the picture quality, which is subjective to noise ratio. There are several donoising techniques were introduced in the way of image processing, but they all work based on the noise ratio. Some techniques were especially designed to deal with less noise ratio of image, where as some other exactly defined to deal with the high noise ratio. So initially finding the ratio of image noise is very important before they treat. Here in below figure 2.G we explained the various levels of image noise from various metrics based are sensor noise, pixel noise, popular canon EOS 10D noise and no noise.

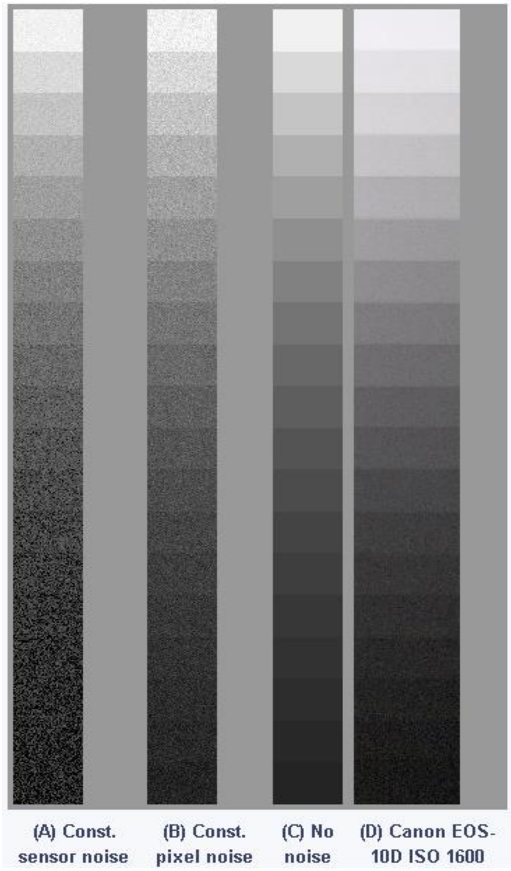


Figure 2.G Various Noise levels of an image

The major technical causes of image noise are:

- ISO
- Sensor Size
- Pixel Density
- Exposure Time
- Shadows

ISO: In general we need the higher ISO to take the image and to shoot the videos in low light. Most of the times, the higher ISO caused to insert the noise in an image or video, due to the dis-comfortable co-ordination of pixels. The selection of ISO is always compatible to the camera capturing pixel density.

Sensor Size: When it comes to noise, **sensor size matters**. Cameras with smaller sensors, such as cell phones and compact cameras have thumbnail-sized sensors, and on these cameras noise can reach unacceptable levels even at ISO 400. By the time you reach ISO 800 or higher, the picture may end up looking like an impressionist painting and lose sharpness, detail and color fidelity. Cameras with larger sensors, such as DSLRs and Mirror less Interchangeable-Lens Compact cameras, produce lower grain at higher ISOs. The larger the sensor is better the grain at comparable speeds.

Pixel Density: A sensor with 14 million pixels (megapixels) will produce more digital noise than an equal-sized sensor with 10 megapixels. That's because, in order to squeeze those extra 4 million pixels, the actual pixel size has to shrink, which means each pixel will let in less light (think of smaller apertures in lenses letting in less like than larger apertures). To compensate, the "gain" is turned up, and this causes distortion. Conversely, a larger sensor with 14MP will produce less grain than a smaller 14MP sensor.

Exposure time: Long exposures can introduce static, which can also be a cause of digital noise.

Shadows: If you are shooting in broad daylight at a higher ISO, the grain might not be so obvious…unless you look at the shadow areas. Grain shows up more against darker subjects or backgrounds. It gets even worse if, using image-editing software such as Adobe Photoshop, you lighten an image. Then the grain in the shadow areas will become even more obvious.

2.6 Types of noisy in image

Noise is the undesirable effects produced in the image. During image acquisition or transmission, several factors are responsible for introducing noise in the image. Depending on the type of disturbance, the noise can affect the image to different extent. Generally this research work focus is to remove certain kind of noise.

So we identify certain kind of noise and apply different algorithms to remove the noise. Image noise can be classified as Photo Electronic noise [30 and 31] (photon noise and thermal noise), Impulse noise (Salt-and-pepper noise) [32], Amplifier noise (Gaussian noise) [33], Shot noise [34], Quantization noise (uniform noise) [35], Film grain [32], on-isotropic noise [36], Multiplicative noise (Speckle noise) and Periodic noise [37].

Photo Electronic noise: This noise is mainly caused by low light levels and astronomy images contained photon arrival statistics. Density function and standard deviations are used to estimate the ratio of noise in images. This noise is signal dependent and can be calculated as:

$$f_{\eta}(m,n) = \eta_{p}(m,n)\sqrt{f_{s}(m,n)} + \eta_{T}(m,n)$$

Because of this noise came from light failure [31], this will effects on whole are of the image. The below figure 2.H is an example of the photo electronic noise with various noise levels like 5, 10, 20.

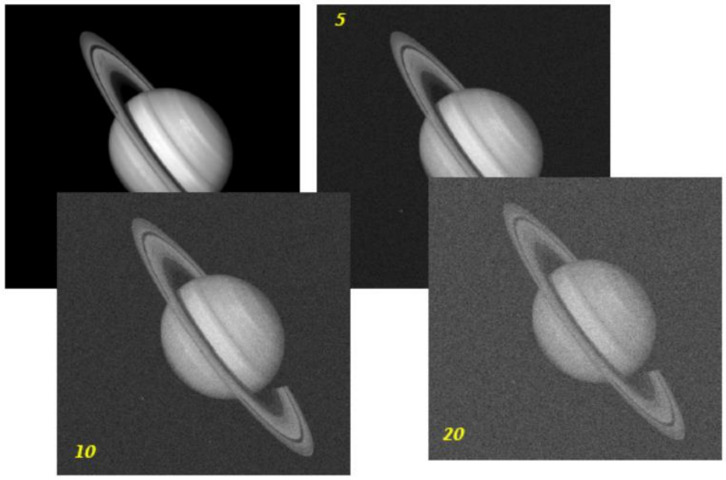


Figure 2.H Photo Electron Noise of an image with various levels

Impulse Noise: This is also called as salt and pepper noise. Due to this noise we have the two problems are data loss or saturation. Salt will specifies the maximum possible impulse (DN_{max}) and pepper specifies that minimum possible (DN_{min}). The whole salt and pepper noise [33] is the combination of DN_{max} and DN_{min} . This can be again caused to loss of line data on image. Figure 2.I shows the salt, pepper noise with line drops on an image.

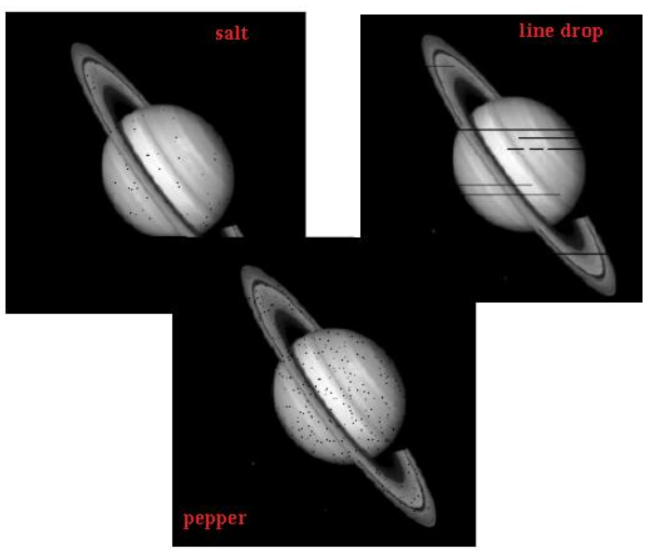


Figure 2.I salt & pepper noise (impulse noise) with line drops

Structured Noise: Structured noise is defined as signal contributions that have a non-random nature and that only affect a certain area of the image. Examples of structured noise include ghosting, ringing, DC artifacts and non-uniform signal distributions [34]. The causes of structured noise are numerous, originating from equipment malfunction such as drift of the magnetic induction, and external interference such as radio frequency (RF) pickup. Usually, with careful engineering design and setup, most sources can be eliminated or minimized.

External RF interference may contribute to both random and structured noise in the MR image. Several authors addressed the need for adequate decoupling between the transmit and receive circuitry to prevent noise interference. Other sources of RF interference may be broadcasting stations and close proximity of electrical equipment such as computers. In practice however, if great care is taken to shield interference using an effective RF cage, these noise sources can be eliminated. Figure 2.J shows an example of image structured noise with vertical strips.

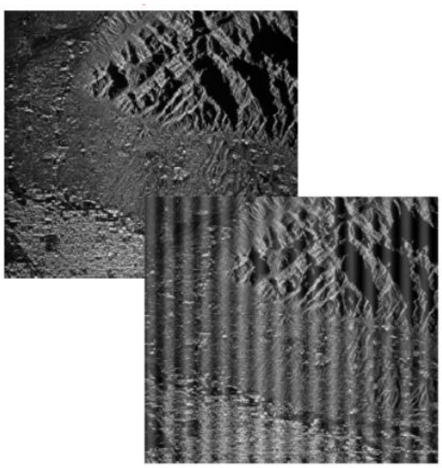


Figure 2.J image structured noise

Amplifier noise (Gaussian noise): This is also called as Gaussian Noise (the popular physics model). This noise has a probability density function [PDF] of the normal distribution. It is also known as Gaussian distribution [37]. It is a major part of the read noise of an image sensor that is of the constant level of noise in the dark areas of the image.

The standard model for this type of noise is additive, Gaussian, and independent of the signal. In modern well-designed electronics, amplifier noise is generally negligible. The most common exception to this is in color cameras where more amplification is used in the blue color channel than in the green channel or red channel leading to more noise in the blue channel. Figure 2.K shows the example Gaussian Model.

Figure 2.K Gaussian model noise with spectacular images

Shot Noise: Shot noise is the noise due to this "counting" of a random number of photons. This noise can be modeled by random value multiplications with pixel values of the image and can be expressed as J = I + n*I Where, J is the shot noise distribution of an image, I is the input image and n is the uniform noise image by mean o and variance v. This noise deteriorates the quality of active radar and

Synthetic Aperture Radar (SAR) images [35]. This noise is originated because of coherent processing of back scattered signals from multiple distributed points. he median filter is very good at removing shot noise. Figure 2.L is the example of shot noise in image processing.

Figure 2.L Shot Noise in image processing

Quantization noise: The discrete wavelet transform (DWT) decomposes an image into bands that vary in spatial frequency and orientation. It is widely used for image compression. Measures of the visibility of DWT quantization errors are required to achieve optimal compression.

Uniform quantization of a single band of coefficients results in an artifact that we call DWT uniform quantization noise; it is the sum of a lattice of random amplitude basis functions of the corresponding DWT synthesis filter [36]. We measured visual detection thresholds for samples of DWT uniform quantization noise in Y, Cb, and Cr color channels.

The spatial frequency of a wavelet is r 2-lambda, where r is display visual resolution in pixels/degree, and lambda is the wavelet level. Thresholds increase rapidly with wavelet spatial frequency. Thresholds also increase from Y to Cr to Cb, and with orientation from low pass to horizontal/vertical to diagonal. Figure 2.M is the example of uniform noise in image processing.

Figure 2.M Image (Holfman) example for Quantization noise or Uniform Noise

Speckle Noise: This is not a noise in an image but noise like variation in contrast. Speckle is basically a form of multiplicative noise, which occurs when a sound wave pulse randomly interferes with the small particles or objects on a scale comparable to the sound wavelength. Speckle noise is defined as multiplicative noise [35 and 37], having a granular pattern it is the inherent property of ultrasound image and SAR image.

Due to incorrect assumption, the ultrasound pulse always travels in a straight line, to and fro from the reflecting interference. Another source of reverberations is that a small portion of the returning sound pulse may be reflected back into the tissues by the transducer surface itself, and generates a new echo at twice the depth. Speckle is the result of the diffuse scattering, which occurs when an ultrasound pulse randomly interferes with the small particles or objects on a scale comparable to the sound wavelength.

Speckle can be modeled in two ways. First one is by using k-Distribution and the other method is by using Rayleigh-Distribution [R-D] [38, 39 and 40].The most widely used method is by using Rayleigh distribution. Rayleigh distribution ratio of variance and mean is constant which exactly the same property of speckle is. This implies that speckle could be modeled by using Rayleigh distribution. Figure 2.M is the example of speckle noise in image processing.

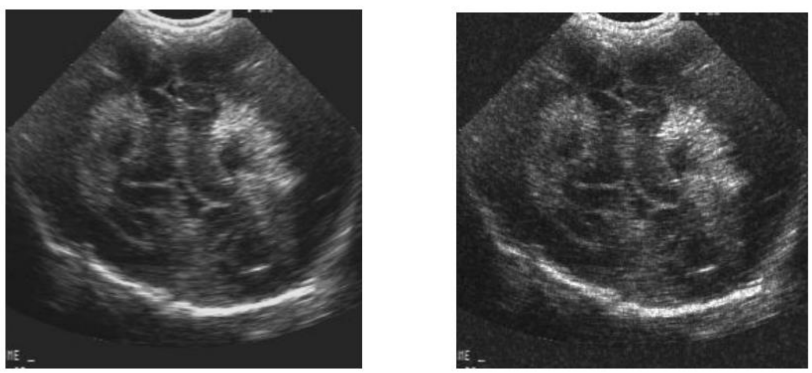


Figure 2.N An Ultra sonic image example with speckle noise in image processing.

2.7 Phases of Digital Image processing

This module describes about what is digital image processing need of digital image processing, Image processing applications and general phases of Image processing in real time.

Digital Image Processing:

It stands for processing or manipulating an image with compute algorithms, mathematical operations by using digital signal processing.

In other words, Image processing is a method to convert an image into digital form and perform some operations on it, in order to get an enhanced image or to extract some useful information from it. It is a type of signal dispensation in which input is image, like video frame or photograph and output may be image or characteristics associated with that image. Usually **Image Processing** system includes treating images as two dimensional signals while applying already set signal processing methods to them.

Advantages of digital image processing are:

- To customize the images
- To visualize the images
- To improvise the quality and standards
- For Image feature extraction(image retrieval)
- For Image feature extraction
- For Image pattern recognition
- For Image data comparison
- For image data transformation

Image Processing applications:

In this real world, there are many applications are using image processing as backbone or else as a part of their applications. Some of them were listed below:

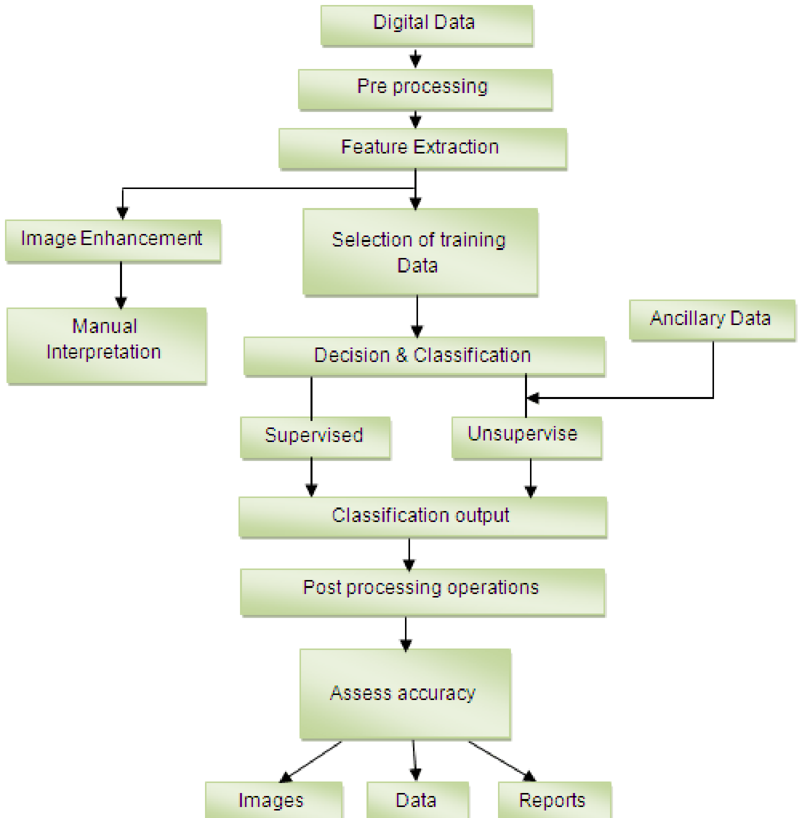
- Image formation or reconstruction
- Image restoration applications
- Image interpretations
- Image Quantification
- Image Transformation
- Image modeling
- Image simulation apps
- Image storage and transmission apps

For all the above processes sake we need to use the image processing and its relevant operations. The above image processing tasks are common among all image processing applications.

Phases of image processing:

If we consider the architecture and work flow of Image processing, it contains some general phases, which are common all most all image processing architectures. Figure 2.O is supporting the same with several phases of image processing.

This architecture is a generic (common parent) for all different image processing architectures. This paragraph concentrates on describing the phases of image processing phases in brief.



2.O Several Phases of Generic Digital image processing architecture

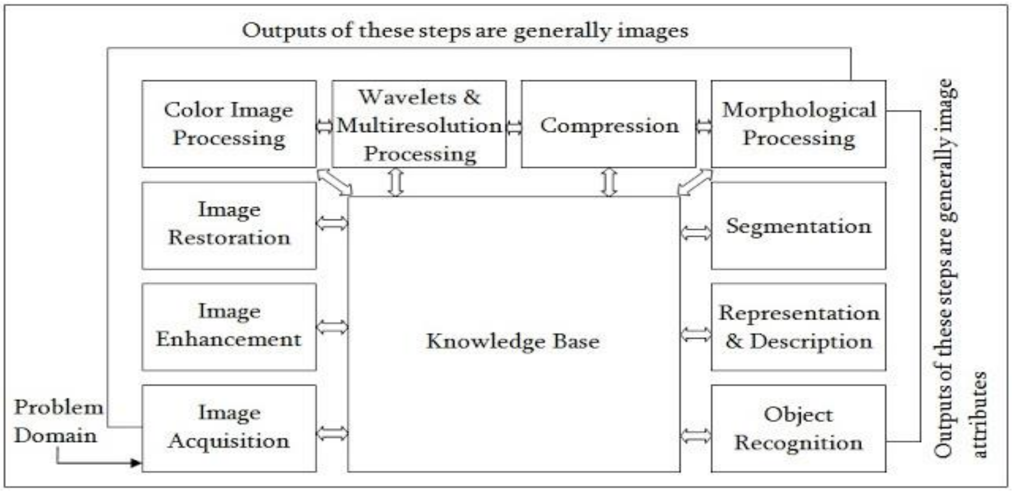
- Initially the digital data is given as an input to the architecture
- Before main processing the input should be pre-processed (transformation, donoising, dissertation etc…)
- Feature extraction from pre-processed input image with image processing tools
- Selection of training data for main processing (or) Manual interpretation
- Image feature classification with the help of classifiers (SVM)
- Classification may be supervised with training data

- ➢ Sometimes unsupervised learning for image processing with ancillary data
- ➢ Image feature classification output
- ➢ With feature classification starting the main processing of image
- ➢ Utilization of respective tools either proved or custom
- ➢ Assessing the accuracy of results from designed model
- ➢ Generating the results as images, Data and report formats

The above steps allow processing any image in a realistic and accurate model.

Block Diagram of image processing with basic steps:

In this section, we would like to discuss about the block diagram of digital image processing with some basic steps. There are some basic steps but as they are basic, all these steps may have sub-steps. The basic steps are described below with a neat diagram 2.P.



2.P Image processing block diagram with basic steps

I. **Image Acquisition:** This is the first step or process of the fundamental steps of digital image processing. Image acquisition could be as simple as being given an image that is already in digital form. Generally, the image acquisition stage involves preprocessing, such as scaling etc.

II. **Image Enhancement:** Image enhancement is among the simplest and most appealing areas of digital image processing. Basically, the idea behind enhancement techniques is to bring out detail that is obscured, or simply to highlight certain features of interest in an image. Such as, changing brightness & contrast etc.

III. **Image Restoration:** Image restoration is an area that also deals with improving the appearance of an image. However, unlike enhancement, which is subjective, image restoration is objective, in the sense that restoration techniques tend to be based on mathematical or probabilistic models of image degradation.

IV. **Color Image Processing**: Color image processing is an area that has been gaining its importance because of the significant increase in the use of digital images over the Internet. This may include color modeling and processing in a digital domain etc.

V. **Wavelets and Multiresolution Processing**: Wavelets are the foundation for representing images in various degrees of resolution. Images subdivision successively into smaller regions for data compression and for pyramidal representation.

VI. **Compression**: Compression deals with techniques for reducing the storage required to save an image or the bandwidth to transmit it. Particularly in the uses of internet it is very much necessary to compress data.

VII. **Segmentation**: Segmentation procedures partition an image into its constituent parts or objects. In general, autonomous segmentation is one of the most difficult tasks in digital image processing. A rugged segmentation procedure brings the process a long way toward successful solution of imaging problems that require objects to be identified individually.

VIII. **Representation and Description**: Representation and descriptional most always follow the output of a segmentation stage, which usually is raw pixel data, constituting either the boundary of a region or all the points in the region itself. Choosing a representation is only part of the solution for transforming raw data into a form suitable for subsequent computer processing. Description deals with extracting attributes that result in some quantitative information of interest or are basic for differentiating one class of objects from another.

IX. **Object Recognition**: Recognition is the process that assigns a label, such as, “vehicle” to an object based on its descriptors.

X. **Knowledge Base**: Knowledge may be as simple as detailing regions of an image where the information of interest is known to be located, thus limiting the search that has to be conducted in seeking that information. The knowledge base also can be quite complex, such as an interrelated list of all major possible defects in a materials inspection problem or an image database containing high-resolution satellite images of a region in connection with change-detection applications.

2.8 Image De-noising Methods

What is image De-noising?

Image de-noising is an integral part of image processing to remove the noise and blur of input images before main processing. In many image processing architectures, this is a prominent preprocessing method. This process effects on result accuracy by improvising the image standards in various terms like brightness, quality, color and pixel border edge dimensions.

Image De-noising is a prominent preprocessing technique in the area of image processing. In general terms, Various Images encounters the different noise problems, their respective donoising methods.

Although several researchers introduced numerous donoising methods, still the image processing is suffering from noise problem. The main reason for this is, image noise is existed in various forms, which is different from image to image. The factors of image noise are different from others. Among the several methods each one is having its own advantages and limitations as well.

Here in this section we discuss about the basic image processing methodologies and their advantages and limitations in detail. We strongly believe that, this review helps us to know about the more information of each donoising technology.

Need of Image De-Noising:

In today digital world, images are playing a vital role in general image processing applications. There are several image processing applications were designed for present and future needs are Space Imaging, Video Processing, Computer Tomography and Sensor data analysis etc.

In general, the image data obtained from several resources (cameras, sensors) contains the noisy. Unexpected weather environments (snowing, raining, and high speed winds), Erroneous instruments, background distortions and some other problems (transmission errors and solid compression techniques) cause to image noising.

If we had given the noisy image as input image to image processing operation, due to the noisy image input the output will be generated as less accurate and not reliable. So each image should be verified and its noise should be removed (de-noising) before they enter to main process as input. So this is necessary to design and apply the respective donoising technique to overcome the problem of image noisy and image processing results in-accuracy.

History of Image De-noising

Image de-noising is a basic and still completely unresolved issue in the area of image processing. Here we discuss about the history of the image de-noising, means the simple evaluation information from beginning.

Spatial and Fourier methods were famous image donoising techniques in image processing in the very beginning of image processing. Later wavelet transform with sparsity and multi-resolution were used for image de-noising, which gives the better results for spatial images and spatial data sets. Due to the better accuracy levels and good distortion techniques it was popular since last two decades. There are several sub research works were designed and succeeded in this area of research.

Although wavelet related articles were published even before to Spatial and Fourier, they were not considered as prominent, because of bit complexity in terms of design and features. But later the famous scholar Donoho introduced the simplified version of wavelet technology to avoid complex image processing problems.

Then onwards the research was diverted towards wavelet technology and its relevant aspects, but not on either Spatial or Fourier. After this revaluation Donoho and Mallet were continued their researches with wavelet transform achieved the great improvement in terms of quality and accuracy.

Wavelet coefficient and data adaptive thresholds [41] were introduced to achieve maximum optimal values of threshold.

Curvelets [42, 43 and 44] were introduced soon after the improvements in the area of image dis-segmentation mechanism. These are multi scaled but non-adaptive techniques, which are inherited from wavelets and designed as extensions and proved their efficiency in scientific computing.

These curvelets are very good in processing point discontinues like wavelets [45, 46 and 47] but poor in processing line discontinues of a noisy image.

Due to this cause, ridgelets were introduced in the area of image processing, which are special members of the family of multi scale orientation-selective transforms [48], which has recently led to a flurry of research activity in the field of computational and applied harmonic analysis.

Image De-noising Methods

There are several methods were defined in the area of image de-noising. Figure 2.P represents the donoising method classification based on the nature of processing. At first level there are two basic approaches to image de-noising, spatial filtering methods and transform domain filtering methods.

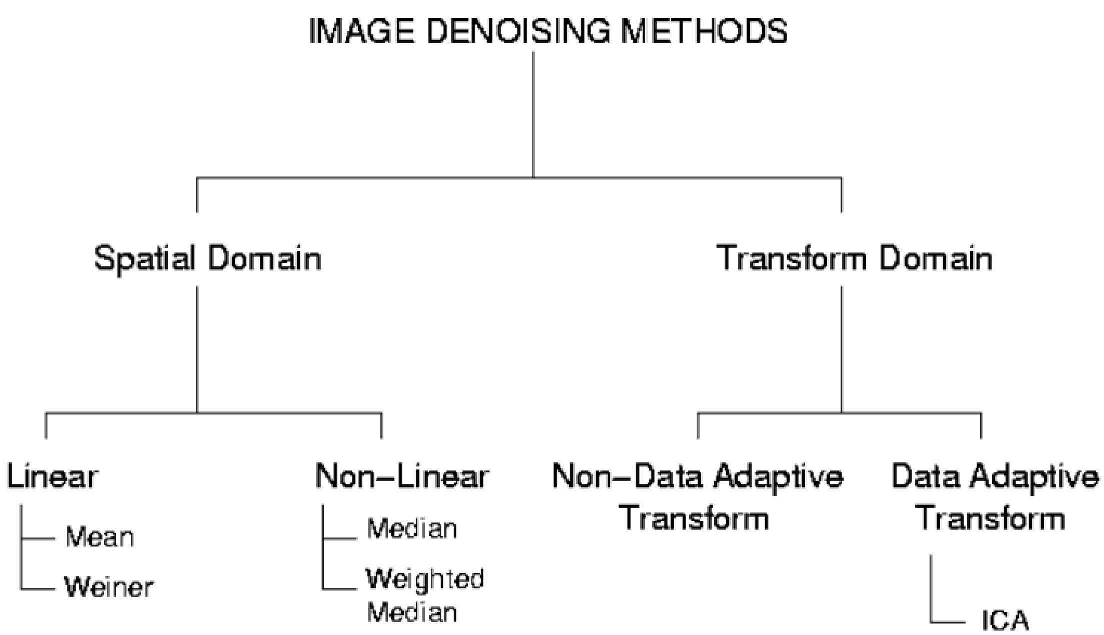


Fig 2.Q Basic image donoising methods classification hierarchy

Spatial dependent De-noising

A traditional way to remove noise from image data is to employ spatial filters [49 and 50]. Spatial filters can be further classified into non-linear [51 and 52] and linear filters [53 and 54].

Non-Linear Filters: With non-linear filters, the noise is removed without any attempts to explicitly identify it. Spatial filters employ a low pass filtering on groups of pixels with the assumption that the noise occupies the higher region of frequency spectrum.

Generally spatial filters remove noise to a reasonable extent but at the cost of blurring images which in turn makes the edges in pictures invisible. In recent years, a variety of nonlinear median type filters such as weighted median [55], rank conditioned rank selection [56], and relaxed median [57] have been developed to overcome this drawback.

Linear Filters: A mean filter is the optimal linear filter for Gaussian noise in the sense of mean square error. Linear filters too tend to blur sharp edges, destroy lines and other fine image details, and perform poorly in the presence of signal-dependent noise.

The wiener filtering [58] method requires the information about the spectra of the noise and the original signal and it works well only if the underlying signal is smooth. Wiener method implements spatial smoothing and its model complexity control correspond to choosing the window size.

To overcome the weakness of the Wiener filtering, Donoho and Johnst one proposed the wavelet based denoising scheme in [59].

Transform based De-Noising:

The transform domain filtering methods can be subdivided according to the choice of the basic functions. The basic functions can be further classified as data adaptive [60 and 61] and non-adaptive [62, 63, 64 and 65]. Non-adaptive transforms are discussed first since they are more popular.

Spatial-Frequency Filtering: Spatial-frequency filtering refers use of low pass filters using Fast Fourier Transform (FFT) [66, 67 and 68]. In frequency smoothing methods [69] the removal of the noise is achieved by designing a frequency domain filter and adapting a cut-off frequency when the noise components are de-correlated from the useful signal in the frequency domain. These methods are time consuming and depend on the cut-off frequency and the filter function behavior. Furthermore, they may produce artificial frequencies in the processed image.

Wavelet domain Filtering operations in the wavelet domain can be subdivided into linear [70, 71 and 72] and nonlinear methods [73 and 74].

Linear Filters: Linear filters such as Wiener filter in the wavelet domain yield optimal results when the signal corruption can be modeled as a Gaussian process and the accuracy criterion is the mean square error (MSE) [75]. However, designing a filter based on this assumption frequently results in a filtered image that is more visually displeasing than the original noisy signal, even though the filtering operation successfully reduces the MSE.

Non-Linear Threshold Filtering: The most investigated domain in denoising using Wavelet Transform is the non-linear coefficient threshold based methods. The procedure exploits sparsity property of the wavelet transform and the fact that the Wavelet Transform maps white noise in the signal domain to white noise in the transform domain. Thus, while signal energy becomes more concentrated into fewer coefficients in the transform domain, noise energy does not. It is this important principle that enables the separation of signal from noise.

The procedure in which small coefficients are removed while others are left untouched is called Hard Threshold method [76 and 77]. But the method generates spurious blips, better known as artifacts, in the images as a result of unsuccessful attempts of removing moderately large noise coefficients [78]. To overcome the demerits of hard threshold, wavelet transform using soft threshold was also introduced.

Non-Adaptive thresholds: VISUShrink [79] is non-adaptive universal threshold, which depends only on number of data points. It has asymptotic equivalence suggesting best performance in terms of MSE when the number of pixels reaches infinity. VISUShrink is known to yield overly smoothed images because its threshold choice can be unwarrantedly large due to its dependence on the number of pixels in the image.

Adaptive Thresholds: SUREShrink [80] uses a hybrid of the universal threshold and the SURE [Stein's Unbiased Risk Estimator] threshold and performs better than VISUShrink. BayesShrink [81] minimizes the Bayes' Risk Estimator function assuming Generalized Gaussian prior and thus yielding data adaptive threshold.

BayesShrink outperforms SUREShrink most of the times. Cross Validation [82] replaces wavelet coefficient with the weighted average of neighborhood coefficients to minimize generalized cross validation (GCV) function [83] providing optimum threshold for every coefficient.

The assumption that one can distinguish noise from the signal solely based on coefficient magnitudes is violated when noise levels are higher than signal magnitudes. Under this high noise circumstance, the spatial configuration [84 and 73] of neighboring wavelet coefficients can play an important role in noise-signal classifications. Signals tend to form meaningful features (e.g. straight lines, curves), while noisy coefficients often scatter randomly.

2.9 Summary

This chapter is composed with the main division is related work. In this Related Work section we discussed about the comprehensive view of basic image definition, image properties, image noising, Types of image noising, need of image transform, phases of image processing, block diagram with basic steps of image processing, image donoising methods for the current research work. This section covered the important information regarding to each of the above concept in detail (text and respective images also).

CHAPTER -3

SLICED RIDGELET TRANSFORM

Objectives of this chapter

3.1 Introduction

3.2 Basic Ridgelet Transform

3.3 Ridgelet Transform Implementation

3.4 Image Slicing and advantages

3.5 Sliced Ridgelet Transform

- ✓ Radon Transform

3.6 Image De-noising with sliced ridgelets

- ✓ Resisting Shift Sensitivity problems of wavelets
- ✓ Threshold value for sliced ridgelet transforms

3.7 Sliced Ridgelet Transform Implementation

3.8 Sliced Ridgelet De-noising Algorithm

3.1 Introduction

In this section we discuss about our proposed sliced ridgelet technology along with the thesis contributions. Initially we describe about the slice ridgelet technology and its terminology. After this, we explore our proposed objectives of this research in a sequential and interlinked manner.

Here we discuss about out new approach sliced ridgelet transform along with its relevant technologies. In first phase of this section, we discuss about the basic ridgelet transform later the ridgelet implementation with equations. Second phase concerns on image slicing, sliced ridgelet transform with implementation. Third phase describes how to overcome the shift sensitivity problems of wavelet, threshold values and sliced ridgelet transform algorithm etc.

3.2 Basic Ridgelet Transform

In general noise in images are classified into two categories are: additive and multiplicative. In order to overcome the problems of image processing with noise images there are several image donoising technologies were introduced. Guassian Radon Noise, Guassian Additive White Noise [18, 83 and 84] and Markov Random fields [84 and 85] are the earlier technologies of image donoising. Wavelets and curvlets are the second generation image donoising technologies.

In the early days of second generation technologies, wavelets were utilized and considered as successful image donoising technologies [86, 87 and 88] and widely used in the areas of image processing, image restoration, image donoising, signal processing, image clustering, feature extraction, pattern recognition and computer graphics etc.

Among the several research contributors of wavelet Donoho [89 and 90] is a prominent person along with his research partners. Wavelet based soft threshold and hard threshold were the major research areas of Donoho and co. This approach gained vast popularity, because of small number of large coefficients was designed for energy of imperative image collection.

First the wavelet transform process will squash the image energy values to small number of large coefficients and collectively the energy values starts from zero. This process ensures that the threshold values set only once with all possible sub versions. In this case the low-frequency coefficients will be simply discarded while processing and they don't even touch the main process threshold [91 and 92]. These are main advantage of wavelet approach, which was originally designed by Donoho.

Many previous approaches have been introduced in this area so far, none of them are resolved the image noising issue up to the expected level of image processing like wavelets.

Although wavelet transform is the better existing technology than others it is also suffering from some transformation problems like Shift sensitivity [93], Poor Directionality and Absence of Phase information [94 and 95].

In recent, ridgelet transforms proven that, they are better than wavelet transforms to implement the de-noising procedure for images in image processing applications.

Ridgelet Transform was especially designed to overcome the limitations of wavelet transform.

Donoho and Candes [96] were proposed and extension to geometric wavelet transform as Ridgelet in their research works in 1999. This is become an efficient mechanism for representing straight line singularities while processing images. The same transform with arbitrary directional selectivity provides a key to the analysis of higher dimensional singularities.

Straight Line Singularities are the big obstacles for image processing, which cannot be resolved by wavelets or curvelets completely. Ridgelet was designed as a sparse expansion for processing functions on sequential spares of object, which are smooth away along imperfect lines. In ridgelet sparse expansion, most image information (data) is packed to small number of chunks [97 and 98]. Each chunk may have the min size zero to max size as the whole image size. This sparse design should be done with only by either invertible or non-redundant transform [99 and 100].

While decomposition of the object wavelet transform will generate the large coefficients at each 2D scale of image, but ridgelet transform generate only less number of packages with large coefficients than wavelets. Handling a lot of coefficients while donoising an image, is too difficult and even cumbersome under some circumstances.

3.3 Ridgelet Transform Implementation

Unlike wavelet transforms, the ridgelet transform processes data by first computing integrals over different orientations and locations. A ridgelet is constant along the lines x1 Cosϴ +x2 Sinϴ = constant always. In the direction orthogonal to these ridges it is a wavelet. Ridgelets have been successfully applied in image de-noising recently to break the limitations of the other image transform technologies.

In this research work, we are introducing the moderated ridgelets are sliced ridgelets, to transform discrete and sliced images of image corpus. Image slicing is another prominent area for generating the sliced images, which are flexible for image processing and feature extractions. This research concentrates on transforming the sliced images with ridgelet transformation with small number for coefficients with large package size.

The two-dimensional continuous ridgelet transform in can be defined as follows. For each a>0, each b ∈Rand each ƛ∈[0,2π), the bivariate ridgelet ƛ(a,b) : R^2→Ris defined as :

ƛ(a, b)=a −1/2 ƛ ((x1 Cosϴ+x2 Sinϴ−b)/a),

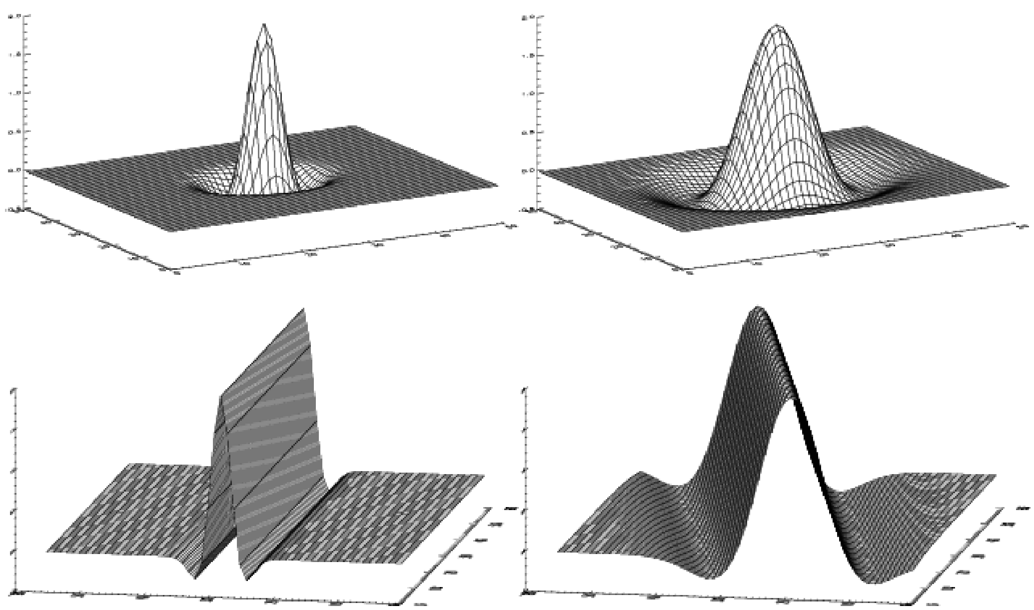
Where ƛ(.) is a wavelet function. A ridgelet is constant along the linesx1cos+x2sin=constant. Transverse to these ridges it is a wavelet. Given an integral bivariate image f(x1, x2), we can define its ridgelet coefficients as (.) is a wavelet function. A ridgelet is constant along the linesx1cos+x2sin=constant. Transverse to these ridges it is a wavelet. Given an integral bivariate image f(x1,x2), we can define its ridgelet coefficients as:

$$R(a, b, \theta) = \int \psi_{a,b,\theta} f(x_1, x_2)\, \mathrm{d}x_1\, \mathrm{d}x_2$$

The ridgelet transform can be represented in terms of the Radon transform. The Radon transform of an image f(x1, x2)is defined as

$$RA(\theta, t) = \int f(x_1, x_2)\delta(x_1 \cos\theta + x_2 \sin\theta - t)\,dx_1\,dx_2.$$

Where the symbol ƛ is the Dirac distribution. So the ridgelet transform is precisely the application of a 1D wavelet transform to the slices of the Radon transform where the angular variable ϴ is constant and t is varying. The below figure 3.A is shows the concept of



3. A Some Ridgelet Examples in image processing

3.4 Image Slicing and advantages

Image slicing [101, 102, 38 and 103] at bit plane level is an important aspect in image processing to increase the result accuracy. Dividing the given image as a set of bit plans caused to make feasible the image analysis is called Image Slicing. In this case each bit of an image would be analyzed with relative importance and implying. This process finalize the number of bits should be used to quantize each pixel value of an image while image clustering or compressing.

Gray level image representation [104] is not good for all de-noise techniques, as they cannot concentrate on straight line singularities. In these circumstances we should implement the whole image in the form of bit plane is a better way than any other. This representation not only concentrates on straight line singularities, but also helps in processing the image at bit plane level [105, 106 and 107], which increases the reliability of process results. Each pixel of an image can be represented as an 8-bit combination, which is also equivalent. Henceforth the image is composed of 8, 1-bit planes ranging from bit plane 0 (LSB) to bit plane 7 (MSB). Figure 3.B shows the basic 8-bit Bit Plan Representation as a block diagram.

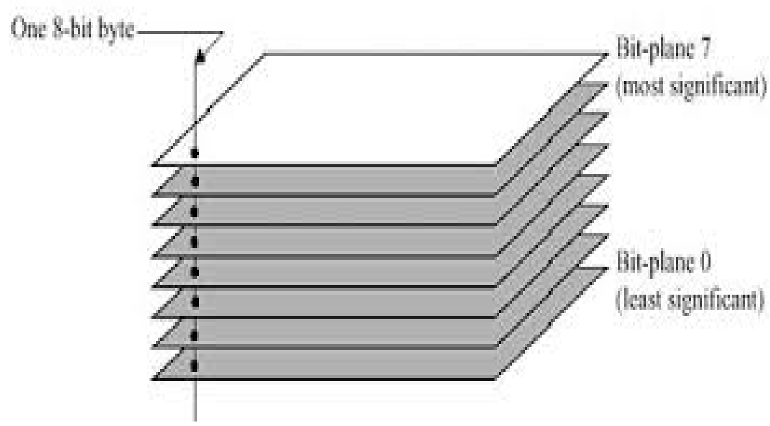


Figure 3.B An 8-bit Bit Plan Representation of Image with properties

In the above bit plane diagram, plane 0 is composed of all lowest order bits as bytes and the plane 7 contains all highest order bits in byte format. If we want to extract an 8 – bit image from the bit plane of an image, we should proceed the input image with a threshold gray-level transformation function that maps all levels between 0 and 127 to one level (e.g. 0)and maps all levels from 129 to 253 to another (e.g. 255).

For Example, for an image with N bit per pixel, and slicing the image with a distinct constant pixel value will effects the results of image processing is called data compression. If we consider there is an image with 8-bits per pixel can represented to bit plans as shown below. In this case zero is the least significant bit (LSB) and 7 is the most significant bit (MSB):

I. 0 which results in a binary image, i.e, odd and even pixels
II. 1 which displays all pixels with bit 1 set: 0000.0010
III. 2 which displays all pixels with bit 2 set: 0000.0100
IV. 3 which displays all pixels with bit 3 set: 0000.1000
V. 4 which displays all pixels with bit 4 set: 0001.0000
VI. 5 which displays all pixels with bit 5 set: 0010.0000
VII. 6 which displays all pixels with bit 6 set: 0100.0000
VIII. 7 which displays all pixels with bit 7 set: 1000.0000

Here in the given below figure 3.C we can observe some examples of sliced images at various bit planes.

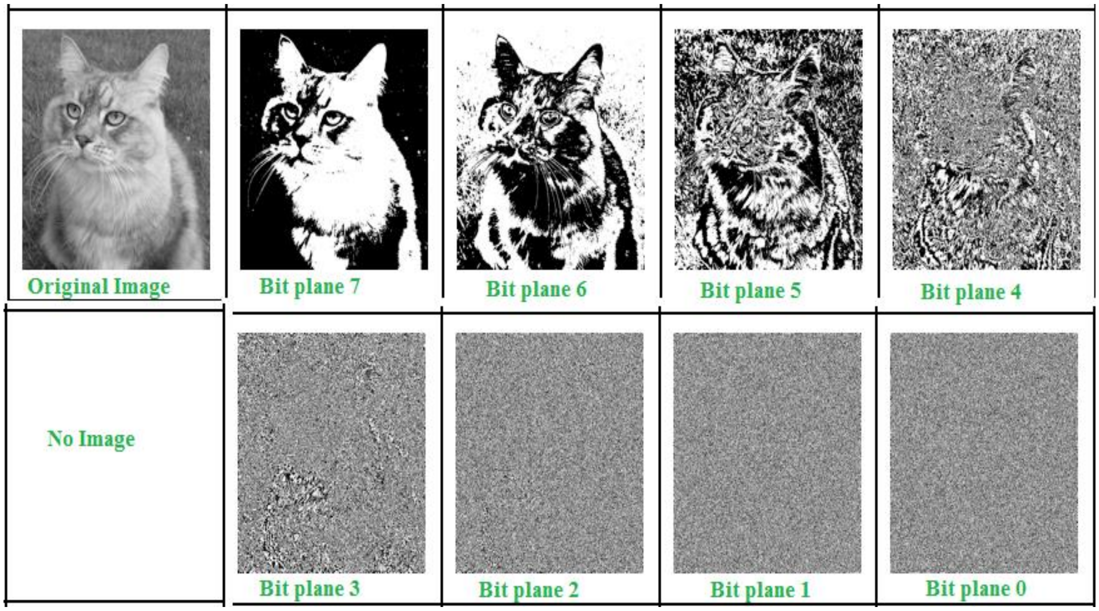


Figure 3.C An 8-bit image and different bit-planes after slicing.

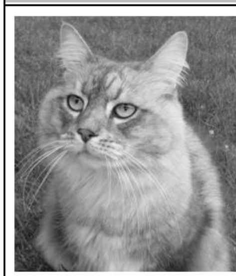
Original Image	(Bit Plane 8 + Bit Plane 7) Mask	Compressed Image	Original File Size	Mask File Size	Compressed File Size
			895K	25K	875K

Figure 3.D An 8-bit image compression with mask 7-bit plane

The above image 3.C represents the pgm image[108 and 109] with 8 different bit planes, which starts from 0 and continues upto 7 (total 8 images). In the next figure 3.D shows that a compressed image with 7 bit plane mask and the size comparison also can be seen. From that comparison we understood that, the compressed image size is less than the original image, even after compressing with the 7 bit plane mask.

Advantages of Image Slicing:

- Highlighting the contribution made by a specific bit.
- For pgm images, each pixel is represented by 8 bits.
- Each bit-plane is a binary image
- Less the size even after compression with bit plane
- Processing done at each bit (pixel) level
- Result Accuracy, scalability and Reliability

3.5 Sliced Ridgelet Transform

Image de-noising is one of the most popular research fields in image processing due to fact that it is extremely difficult to form a general global de-noising scheme effective for all types of noise as well as all types of images. A common problem in image de-noising is the blurring of the prominent edges [110] in the image which can caused is crepancies when the de-noising operation is combined with other operations such as image edge detection and segmentation.

Sliced ridgelets are the ridgelets which are enriched for working at sliced images with different bit plane level. Wavelets are mainly targeted for processing object isolated singularities [111 and 112] and ridgelets are very impressive in the area of processing lines singularities along with the point cuts of the given image.

Initially sliced ridgelet transform will create a digital pyramid for the given digital image. This digital pyramid [113] is having the constant number of orientations for supporting feature extraction.

Let G is the dyadic square value [114] as G = $[P_1/2^s, (P_1+1)/2^s]$ X $[P2/2^s, (P^2+1)/2^s]$ and T is the collection of all dyadic squares. We write for the collection of all dyadic T_s squares of scale. Associated to the squares G ϵ G_s we construct a partition of energy as follows. With a W nice smooth and transport to all squares w at scale, producing a collection of windows.

We also let denote the transport operator T_Q acting on functions as:

$$(T_Q g)(x_1, x_2) = 2^s g(2^s x_1 - k_1, 2^s x_2 - k_2)$$

The notations with slice ridgelet transform as:

$$f w_Q = \int \langle f, w_Q T_Q \psi_{a,b,\theta} \rangle T_Q \psi_{a,b,\theta} \frac{da}{a^3} db \frac{d\theta}{4\pi}$$

In this case the orientations will be independent from scale and orientation count will be inverse proportional to scale.

Wavelets also implemented the pyramid process but failed to stop the creation of core scales while setting the values of donoising. To overcome this problem and to make sliced ridgelet transform as defect free we implemented **bivariate rotation control system**. This is used to avoid the problem of shift sensitivity, which used to arise when working with wavelets as described in related work.

This bivariate rotation control system will takes an image and decomposes the original n by n image into smoothly overlapping blocks of side length pixels b in such a way that the overlap between two vertically adjacent blocks is a rectangular array of size b by b/2; we use overlap to avoid blocking artifacts. For an n by n image, we count such 2n/b blocks in each direction. The partitioning introduces redundancy, as a pixel belongs to4 neighboring blocks. We present two competing strategies to perform the analysis and synthesis:

1) The block values are weighted (analysis) in such a way that the co-addition of all blocks re-produces exactly the original pixel value (synthesis).

2) The block values are those of the image pixel values (analysis) but are weighted when the image is reconstructed (synthesis).

There are intermediate strategies and one could apply smooth windowing at both the analysis and synthesis stage as discussed above, for example. In the first approach, the data are smoothly windowed and this presents the advantage to limit the analysis artifacts traditionally associated with boundaries. The drawback, however, is a loss of sensitivity. Indeed, suppose for sake of simplicity that a vertical line with intensity level intersects a given block of size. Without loss of generality assume that the noise standard deviation is equal to 1.

These sliced ridgelet transform will concentrates on both, object isolated singularities and the processing lines singularities along with the point cuts. For example earlier image processing applications need to implement the both wavelets and curvelets /

ridgelets for whole processing. Our sliced ridgelet transform is designed to alleviate the burden of implementing the both methods.

- Wavelets → ƛ scale, point-position
- Ridgelets → ƛ scale, line-position
- Sliced Ridgelets → ƛ scale, (point-position , line-position)

Unlike ridgelets and wavelets, our sliced ridgelet will considers the 2-D, and those lines are related through Radon transform [115, 116 and 117]for efficiency, so our ridgelets and sliced ridgelets were inter connected through Radon transform.
Candes at el in 1998 he defined the ridgelet transform as :

$$R_f(a,b,\theta) = \int \psi_{a,b,\theta}(x) f(x) dx$$

By considering the same functionality we defined the sliced ridgelet transform as:

$$\psi_{a,b,\theta}(x) = a^{\frac{1}{2}} \psi\left(\frac{x_1 \cos(\theta) + x_2 \sin(\theta) - b}{a}\right)$$

The above formula is describing that a sliced ridgelet is constant along the lines x1 CosΘ + x2 SinΘ = constant always for the given bit planes a, b and for threshold value Θ. The sliced ridgelet transform is optimal to find both points and lines of the size of the image. To detect line segments, a partitioning must be introduced. The image is decomposed into blocks, and the ridgelet transform is applied on each block.

In order to perform the ridgelet transform we implemented the two given below methods as Radon transform and Fourier transform. These methods will be the integral part of our sliced ridgelet transform to implement the sliced image processing.

Radon transform

As specified above our sliced ridgelet transform is using the Radon transform technique for 1-D and 2-D for Fourier and wavelet transformation sake. Various image layers and their packed pixel content will be calculated by the approximate Radon transform formula is:

Coefficients can be calculated as:

$$w_{j+1}(\vartheta,\varphi) = c_j(\vartheta,\varphi) - c_{j+1}(\vartheta,\varphi)$$

Hence the Radon transform function is:

$$\hat{\psi}_{\frac{l_c}{2^j}}(l,m) = \hat{\phi}_{\frac{l_c}{2^{j-1}}}(l,m) - \hat{\phi}_{\frac{l_c}{2^j}}(l,m)$$

In the recursive manner:

$$\hat{w}_{j+1} = \hat{h}_j \widehat{G}_j$$

$$\text{where} \quad \widehat{G}_j(l,m) = \begin{cases} \frac{\hat{\psi}_{\frac{l_c}{2^{j+1}}}(l,m)}{\hat{\phi}_{\frac{l_c}{2^j}}(l,m)} & \text{if } l < \frac{l_c}{2^{j+1}} \quad \text{and} \quad m = 0 \\ 1 & \text{if } l \geq \frac{l_c}{2^{j+1}} \quad \text{and} \quad m = 0 \\ 0 & \text{otherwise} \end{cases}$$

Here, $\hat{G}_j(l,m) = 1 - \hat{H}_j(l,m)$

In the above given formula set, most of the Radon transforms not have been the invertible transforms for digital images. Meanwhile the Radon transform theory [117 and 119] introduced another new interesting topic of transform with by inheriting periodization.

After this invention, Radon Transform has been updated to Slice Support Radon Transform (SSRT), to provide the better support for sliced ridgelet transform. This Slice Support Radon Transform is defined as summations of image pixels over a certain set of "lines." Those lines are defined in a finite geometry in a similar way as the lines for the continuous Radon transform in the Euclidean geometry [120].

The SSRT for sliced ridgelets was customized as shown below:

$$r_k[l] = FRAT_f(k, l) = \frac{1}{\sqrt{p}} \sum_{(i,j)\in L_{k,l}} f[i, j].$$

$$L_{k,l} = \{(i, j): j = ki + l \pmod p,\ i \in Z_p\}, \quad 0 \le k < p,$$
$$L_{p,l} = \{(l, j): j \in Z_p\}.$$

Here, $L_{k,l}$ denotes the set of points that make up a line on the Z^2_plattice , or, more precisely and i, j are the temp values , p is a prime number and k is the number of vertical lines. The measurable sliced ridgelet co-efficient of an image object f are given by analysis of the Radon transform via:

$$R_f(a,b,\theta) = \int Rf(\theta,t)\psi(\frac{t-b}{a})dt$$

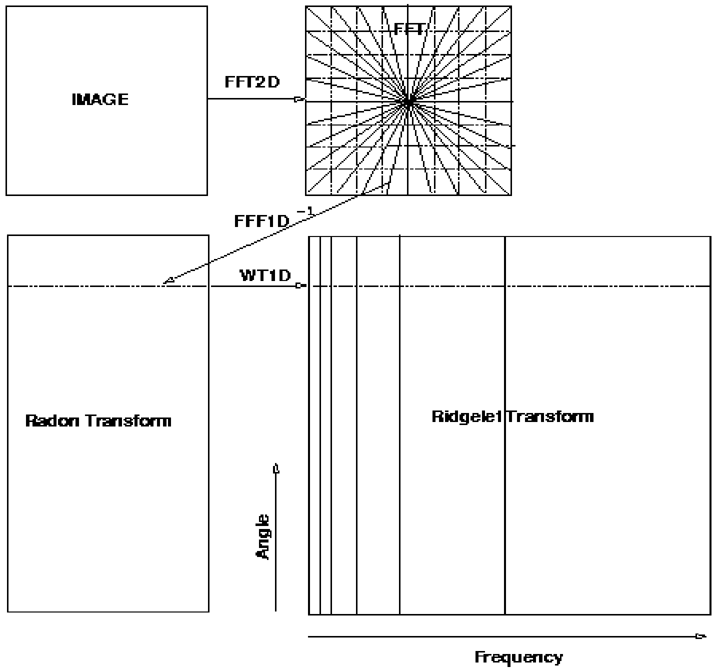


Figure 3.E Radon Transform for Sliced Ridgelets

3.6 Image De-noising with sliced ridgelets

Wavelets and Curvlets transform will analyze the smooth and edge objects with closet suitable sparsity of representation. This process is quite similar to Guassian method of noise removal processing. Our sliced ridgelet transform will compress the image energy into smaller number of ridgelet coefficients. If we compared this with wavelets, they are totally different from this approach, as they generate the huge number of coefficients to compress the image energy on the edges on every scale of the2D wavelet decomposition [123 and 124]. This is cumbersome because of, the reconstruction of image energy need the huge turn around work in this process. This will mainly effects on scalability of image donoising process when compared with others like ridgelets and curvelets.

Resisting Shift Sensitivity problems of wavelets

As we are insisting radon transform as an integral part of sliced ridgelet transform, this will discrete the image energy into Fast Fourier Transform (FFT). The sliced ridgelet transform with radon will be described as follows:

- Calculate the image 2D Fast Fourier Transform
- Populate the square lattice and polar lattice with the obtained values of FFT
- Predicate the angular line level 1D inverse FFT
- Run the general ridgelet transform of angular lines to get the sliced coefficients.

Since the general ridgelet is not shift invariant, it is better to apply the dual-tree complex wavelet in the ridgelet transform so that we can have what we call complex ridgelets. This can be done by replacing the 1D general ridgelet with the 1Ddual-tree complex wavelet transform in the last step of the sliced ridgelet transform. In this way, we can combine the good property of the ridgelet transform with the approximate shift invariant property of the dual-tree complex wavelets.

Threshold value for sliced ridgelet transforms

The threshold value for the sliced ridgelet transform is similar to the curvelet threshold [14]. One difference is that we take the magnitude of the sliced ridgelet coefficients when we do the threshold. Let $y_{\#}$ be the noisy ridgelet coefficients. We use the following hard threshold rule for estimating the unknown ridgelet coefficients. When $|y_{\#}|>= k\tilde{}$, we let $|\hat{}y= |y_{\#}$. Otherwise, $|\hat{}y=0$. Here, $k\tilde{}$ is approximated by using Monte-Carlo simulations. The constant K is used as dependent on the noise standard deviation. When the noise standard deviation α is less than30, we use k=5 for the first decomposition scale and k=4 for other decomposition scales. When the noise standard deviation α is greater than 30, we use k=6for the first decomposition scale and k=5 for other decomposition scales. The value of k in the threshold process is selected by experiments. We have tried different values for k, and the best value has been selected for k.

3.7 Sliced Ridgelet Transform Implementation

The sliced ridgelet transform implementation for digital images at lines, we use this approach as follows

$$L^{\omega}_{[p,q]} = \left\{ (x_1, x_2) \in \mathbb{Z}^2 \middle| |qx_1 - px_2| \leq \frac{\omega}{2} \right\}$$

With [p, q] ϵ Z2 the direction of the Radon projection and w, a function of (p, q), the arithmetical thickness. Reveilles introduced the discrete analytical lines defined as 0 <= qx - py + r < w. In this thesis, since we need central symmetry, we chose a variant of the closed discrete analytical lines, defined as 0<= qx – py <= w.

It is easy to see that the closed discrete analytical lines Lw [p, q] have a central symmetry regardless of the value of w. Moreover, the discrete analytical line can easily be extended to higher dimensions as discrete analytical hyper planes.

The arithmetical thickness w is an important parameter that controls, among other things, the connectivity of the discrete lines: let's consider the closed discrete analytical line Lw [p, q] and its Euclidean counterpart L [p, q]: qx1 - px2 = 0, then:

- ✶ For w< max (|p| , |q|), Lw [p, q] is not connected;
- ✶ For w = max (|p| , |q|), Lw [p, q] is 8-connected.

This is called the closed naive line. It is directly related to the distance d1 since:

$$L_{[p,q]}^{\max(|p|,|q|)} = \left\{ M \in \mathbb{Z}^2 \middle| d_1\left(M, \mathcal{L}_{[p,q]}\right) \leq \frac{1}{2} \right\}$$
$$\text{with } d_1(A,B) = \left|x_1^A - x_1^B\right| + \left|x_2^A - x_2^B\right|$$

- ✶ For w< max (|p| , |q|), Lw [p, q] is 8 connected;
- ✶ For w = max sqrt(|p| , |q|), Lw [p, q] is 8-connected.

$$L_{[p,q]}^{\sqrt{p^2+q^2}} = \left\{ M \in \mathbb{Z}^2 \middle| d_2\left(M, \mathcal{L}_{[p,q]}\right) \leq \frac{1}{2} \right\}$$
$$\text{with } d_2(A,B) = \sqrt{\left(x_1^A - x_1^B\right)^2 + \left(x_2^A - x_2^B\right)^2}$$

These results are direct consequence of a well-known result in discrete analytical geometry and more recent studies on distances.

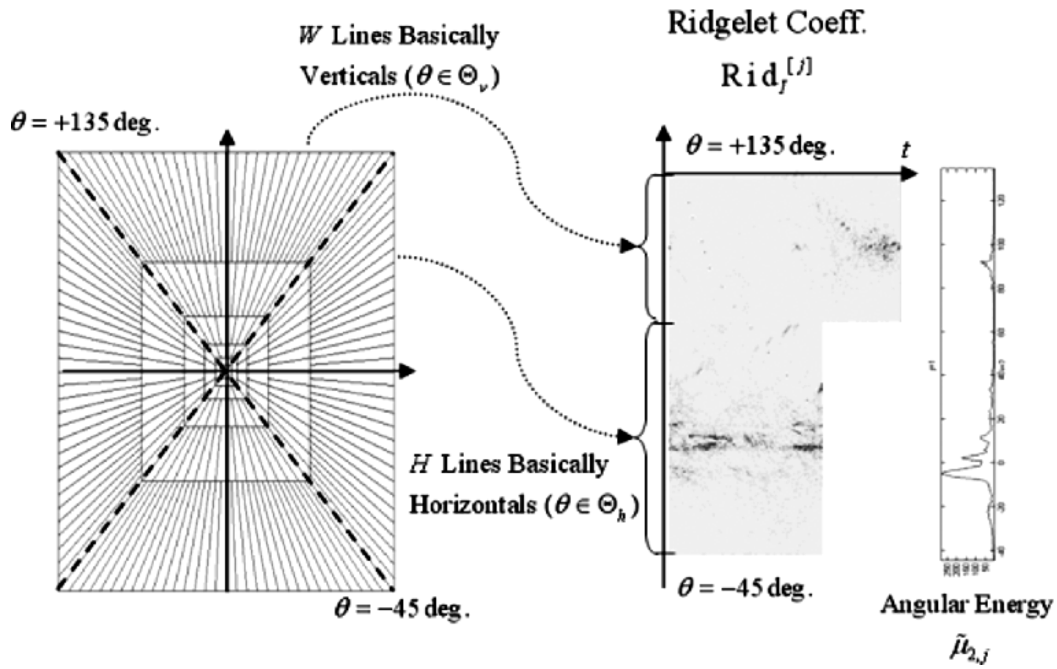
The fact that these lines can be defined with help of distances makes a direct link with mathematical morphology. We use the Fourier domain for the computation of Fast Fourier Radon transform: Fourier coefficients of s are extracted along the discrete analytical line $L^w[p, q]$.

$$P^{\omega}_{[p,q]}s = \bigcup_{k \in \mathbb{Z}+} \widehat{s}(f_1^k, f_2^k) \text{ such that } \left|qf_1^k - pf_2^k\right| \leq \frac{\omega}{2}$$

and we take the 1-D inverse FFT of Pw [p, q]s on each value of the direction [p, q]. Formally, our discrete analytical Radon transform is defined by:

$$R^{\omega}s([p,q],b) = \sum_{k=0}^{K-1} P^{\omega}_{[p,q]}s(k).e^{2\pi j \frac{k}{K} b} \text{ with } K \text{ length of } L^{\omega}_{[p,q]}$$

We must dene the set of discrete directions [p, q] in order to provide a complete representation. The set of line segments must cover the entire square lattice in the Fourier domain. For this, we define the directions [p, q] according to pairs of symmetric points from the boundary of the 2-D discrete Fourier spectra as shown in figure 3.F.



3. F Sliced Ridgelet Transformation for line Singularities

3.8 Sliced Ridgelet De-noising Algorithm

Begin

Input: digital image corpus with noise

Output: de-noised digital image corpus

Process:

Step1: Start image partition as horizontal and vertical RxR blocks

Step2: Arrange the vertical overlapping for adjacent block as R/2xR

Step3: Arrange the horizontal overlapping for adjacent block as RxR/2

Step4: for Each (block: RxR) {

- *Apply image slicing*
- *Get smaller number of coefficients*
- *Apply Fast Fourier Transform (FFT)*
- *Apply Radon Transform*
- *Set Threshold value*
- *Run sliced ridgelet transform*

}

Step5: Collect the same location pixel values at donoising image

Step6: Generate process phase wise result report and display them

End

We call this algorithm as Sliced RidgeletShrink, while the algorithm using the ordinary RidgeletShrink. The computational complexity of Sliced RidgeletShrink is similar to that of RidgeletShrink by using the scalar wavelets. The only difference is that we replaced the 1D ridgelet transform with the 1D dual-tree sliced ridgelet transform. The amount of computation for the 1D dual-tree sliced ridgelet is twice that of the 1D scalar wavelet transform. However, other steps of the algorithm keep the same amount of computation.

Our experimental results show that sliced RidgeletShrink outperforms VisuShrink, RidgeletShrink, and wiener2filterfor all testing cases. Under some case, we obtain 1.30 dB improvements in PSNR over RidgeletShrink [124 and 125]. The improvement over VisuShrink is even bigger for de-noising all images. This indicates that Sliced RidgeletShrinkis an excellent choice for de-noising natural noisy images. This whole process is explained in detail of the experiments section

CHAPTER - 4

LITERATURE REVIEW

Objectives of this chapter

4.1 Wavelet Transforms

4.2 Wavelet Transforms Versus Fourier Transforms

- Wavelet Applications
- FBI Fingerprint Compression

4.3 Curvelets Transformation

4.4 From Classical Wavelets To Curvelets

4.5 How to Transfer This Idea to the Curvelets Construction

4.6 Recent Curvelets based Applications

- Image Processing
- Fluid Mechanics
- Partial differential equation (PDE)

4.7 Ridgelet Transformation

4.8 Sparse Geometrical Image Representation

- The Continuous Ridgelet Transform

4.9 The Recto Polar Ridgelet transform

4.10 The Orthonormal Finite Ridgelet Transform

4.11 Local Ridgelet Transforms

4.1 Wavelet Transforms

The wavelet transform has become a useful calculating tool for different types of signal and image processing applications. To the raw signal Mathematical transformations are applied to obtain further information from that signal which is not readily available in the raw signal. Most of the signals in practice are TIME-DOMAIN signals in their raw format.

Example, for the compression of digital image files the wavelet transform is very useful. Smaller files are important for storing images using less memory and for transmitting images faster and more reliably. There are a number of transformations that can be applied, among which the Fourier transforms [126] are probably by far the most popular.

Digitally scanned fingerprint images can be compressed by using wavelet transforms which are used by FBI. In addition, JPEG2K (the newer JPEG image file format) is based on wavelet transforms. In many cases, the most distinguished information is hidden in the frequency content of the signal. Figure 4.A describes the process flow diagram of wavelet transform.

For 'cleaning' signals and images (reducing unwanted noise and blurring) Wavelet transforms are also useful. We all know that the frequency is something to do with the change in rate of something.

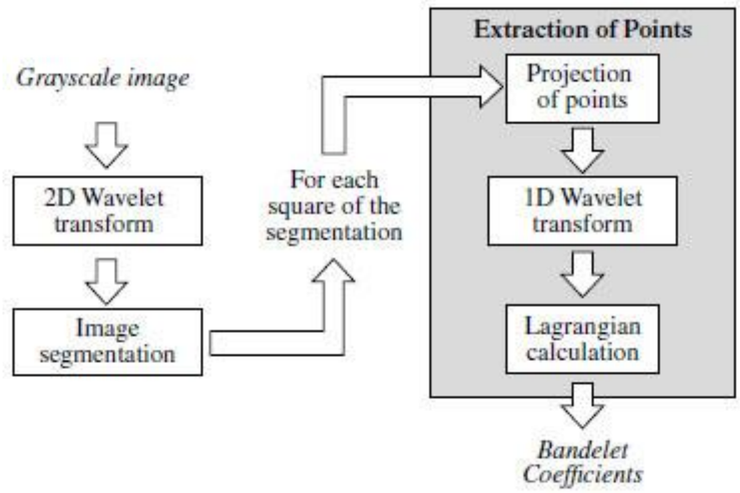


Figure 4.A Wavelet Transform with Gray Scale Image

If something (a mathematical or physical variable would be the technically correct term) changes rapidly, we say that it is of high frequency, where as if this variable does not change rapidly, i.e., it changes smoothly, we say that it is of low frequency. If this variable does not change at all, then we say it has zero frequency [127 and 128], or no frequency.

There are two basic types of wavelet transform. First type of wavelet transform is easily reversible designed in that way the original signal can be easily recovered after it has been transformed. Image compression and cleaning can be done by this kind of wavelet transform (noise and blur reduction [129 and 130]).Typically, the wavelet transform of the image is first computed, to obtain a new image, the wavelet representation is then modified appropriately, and then the wavelet transform is reversed (inverted [131, 132 and 133]).

The second type is for signal analysis of wavelet transform is designed; for example, to detect faults in machinery from sensor measurements, to study EEG or other biomedical signals, to determine how the frequency content of a signal evolves over time. In these cases, a modified form of the original signal is not needed and the wavelet transform need not be inverted, but requires a lot of computation time in comparison with the first type of wavelet transform.

The frequency is measured in "Hertz" and also measured in cycles/second. The electric power we use in our daily life is 50 Hz and in the US is 60 Hz. This means that if you try to plot the electric current, it will be a sine wave passing through the same point 50 times in 1 second. Now, look at the following figures. The first one is a sine wave at 3 Hz, the second one at 10 Hz, and the third one at 50 Hz.

A) Fourier Transforms

Fourier transform's [134, 48, 135 and 136] is used to measure the frequency of the signal, Fourier's representation of functions as a superposition of sins and cosines.

The Fourier transform's for its frequency content, it utility lies to analyze a signal in the time domain. To obtain the frequency-amplitude representation of that signal the Fourier transforms of a signal in time domain is taken. Each sine and cosine function at each frequency of Fourier coefficients of the transformed function represent the contribution, for that the signal can then be analyzed for its frequency content.

We now have a plot with one axis being the frequency and the other being the amplitude. This plot tells us how much of each frequency exists in our signal.

The frequency axis starts from zero, and goes up to infinity. Amplitude value will be available to each every frequency. For example, if we take the FT of the electric current that we use in our houses, we will have one spike at 50 Hz, and nothing elsewhere, since that signal has only 50 Hz frequency component. No other signal, however, has a FT which is this simple. For most practical purposes, signals contain more than one frequency component. The following shows the FT of the 50 Hz signal:

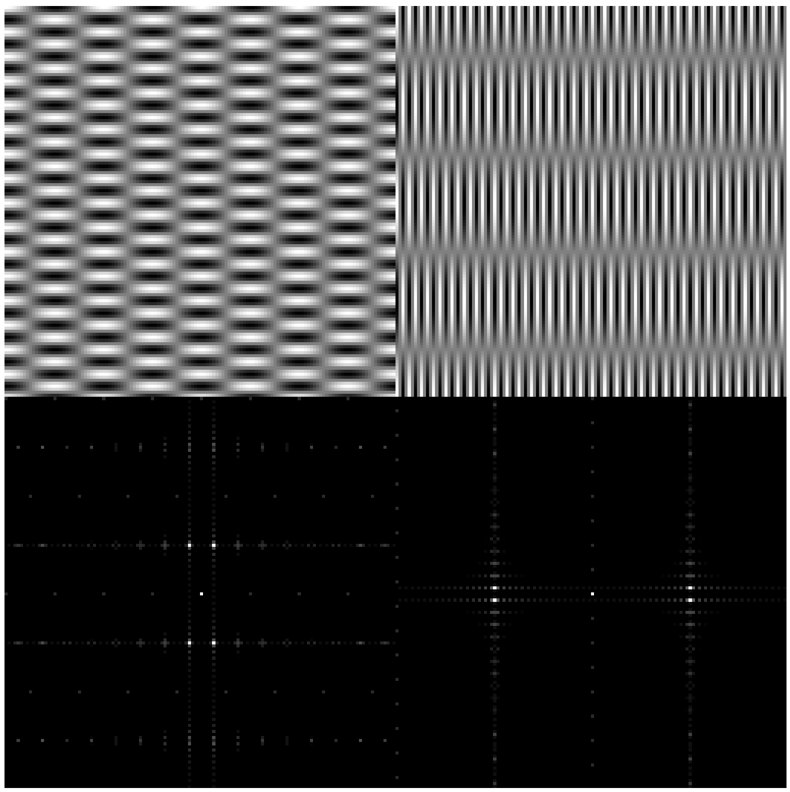


Figure 4.B The General Phases of Fourier Transform

B) Why Do We Need The Frequency Information?

Often times, the details which see in the time-domain can be seen in the frequency domain. Let's give an example from biological signals. Suppose we are looking at an ECG signal. The typical shape of a healthy ECG signal is well known to cardiologists. Any significant deviation from that shape is usually considered to be a symptom of a pathological condition. In the original time domain signal, the pathological condition may not always be quite. On strip-charts to analyze ECG signals Cardiologists record all the time-domain ECG [87] signals. The pathological condition can test by using the new computerized ECG recorders or analyzers. Computerized ECG also utilizes the frequency information. A pathological condition can sometimes be diagnosed more easily when the frequency content of the signal is analyzed.

This, of course, is only one simple example why frequency content will be useful. Now a day's all type of engineering branches using Fourier transforms. Although Fourier transforms is mainly the most popular transform being used. Many engineers and mathematicians are using many other transforms. Hilbert transform [91], Radon Fourier transform [118], Wigner distributions, the short-time Transform, and of course our featured transformation, the wavelet transform, constitute only a small portion of a huge list of transforms that are available at engineer's and mathematician's disposal. In own area of applications there are mostly used transformation technique, with advantages and disadvantages, and the wavelet transform (WT) is no exception. Between the raw and processed (transformed) signals, reversible transform allows to move back and forward. However, only any one of them is available at any given time. In the time-domain signal there is no availability of frequency information, and no time information is available in the Fourier transformed signal.

As we will see soon, the results depends on that we are using application, and the nature of the signal in hand. Recall that the FT gives the frequency information of the signal, which means that it tells us how much of each frequency exists in the signal, but it does not tell us when in time these frequency components exist. This information is not required when the signal is so called stationary.

Let's take a closer look at this stationary concept very deeply, since it is importance in signal analysis. Stationary signals are called which signal of content frequency does not change in time. In other words, the frequency content of stationary signals does not change in time. In this case, one does not need to know at what times frequency components that will exist, since all frequency components exist at all times. For example the following signal

x(t)= cos(2*pi*10*t)+cos(2*pi*25*t)+cos(2*pi*50*t)+cos(2*pi*100*t)

is a stationary signal, because it has frequencies of 10,15, 25, 35,50, and 100 Hz at any given time instant. This signal is plotted below as shown in 4.C:

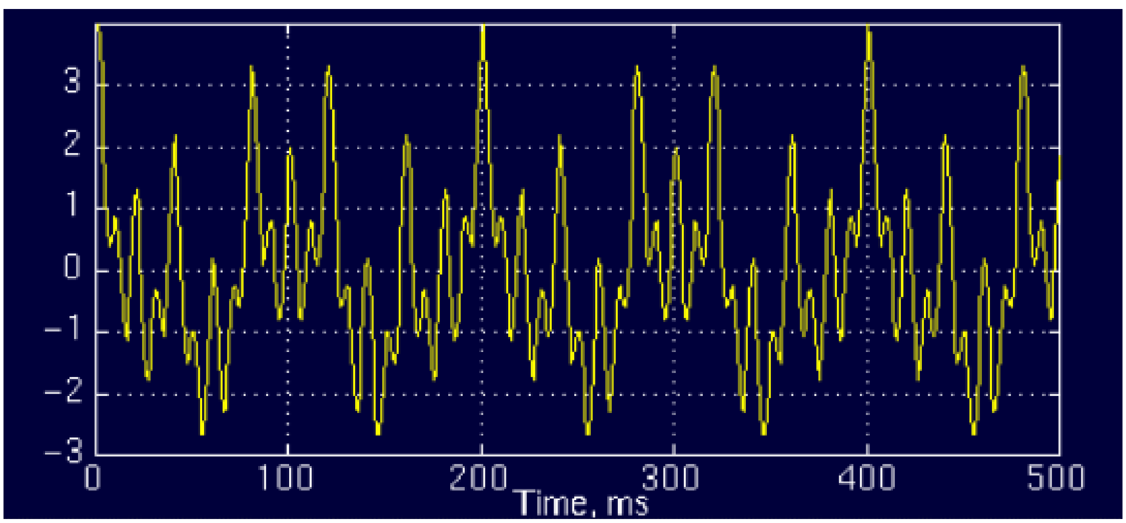
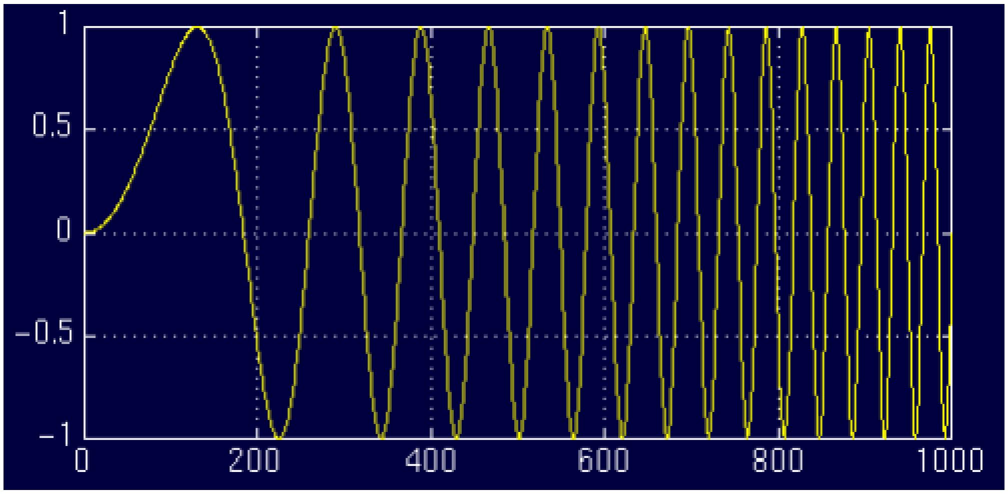


Figure 4.C Stationary Signal Frequency representation of FT

Contrary to the signal in above Figure, the following signal is not stationary. Below Figure 4.D plots a signal whose frequency constantly changes in time. This signal is known as the "chirp" signal. This is a non-stationary signal.



4.D Chip Signal Frequency representation of FT

4.2 Wavelet Transforms Versus Fourier Transforms

The fast Fourier transform (FFT) and the discrete wavelet transform (DWT) [137] are both linear operations that generate a data structure that contains log2 n segments of many different lengths, usually filling and transforming it into a different data vector of length 2n. The mathematical properties of the matrices involved in the transforms are same as well.

For both the FFT and the DWT, inverse transform matrix is the transpose of the original. To a different domain both transforms can be viewed as a rotation in function space as a result. For the new FFT contains basis functions that are sins and cosines. For the wavelet transform, this new domain contains more complicated basis functions called wavelets.

There is another similarity between both transforms. The basic functions are localized in frequency, making mathematical tools like power spectra and scale grams useful at picking out frequencies and calculating power distributions.

A) Wavelet Applications

The following applications show just a small sample of what researchers can do with wavelets. In the early 1980s, David Marr began work at MIT's Artificial Intelligence Laboratory on artificial vision for robots. He is an expert on the human visual system [138] and his goal was to learn why the first attempts to construct a robot capable of understanding its surroundings were unsuccessful. Marr believed that it was important to establish scientific foundations for vision, and that while doing so; one must limit the scope of investigation by excluding everything that depends on training, culture, and so on, and focus on the mechanical or involuntary aspects of vision. This low-level vision is the part that enables us to recreate the three-dimensional organization of the physical world around us from the excitations that stimulate the retina.

B) FBI Fingerprint Compression

Between 1924 and today, the US Federal Bureau of Investigation has collected about 30 million sets of fingerprints. The archive consists mainly of inked impressions on paper cards. Facsimile scans of the impressions are distributed among law enforcement agencies, but the digitization quality is often low. Because a number of jurisdictions are experimenting with digital storage of the prints, incompatibilities between data formats have recently become a problem. This problem led to a demand in the criminal justice community for a digitization and a compression standard. In 1993, the FBI's Criminal Justice Information Services Division developed standards [138] for fingerprint digitization and compression in cooperation with the National Institute of Standards and Technology, Los Alamos National Laboratory, commercial vendors, and criminal justice communities

4.3 Curvelets Transformation

Most natural images/signals exhibit straight line-like edges, those discontinuities across. In scientific and engineering fields the applications of wavelets has become more popular. For representing point singularities the traditional wavelets will work very properly since they ignore the geometric properties of structures and do not exploit the regularity of edges. Therefore, wavelet-based types one is compression, second is de-noising, or structure of the extraction become computationally inefficient for geometric features with line and surface singularities.

In many remote sensing and mapping applications, the fusion of multispectral and panchromatic images is a very important issue. In this regard, by using fused image's quality of the image classifier is affected in the field of classification of satellite image. Now-a-days there are many image fusion techniques and software tools have been developed. The well-known methods include the Brovey, the IHS (Intensity, Hue, and Saturation) color model, the PCA [139] (Principal Components Analysis) method, and the wavelet based method based on wavelet. Assessment of the quality of fused images another important issue is assessment of the quality of fused images. Wald et al. proposed an approach utilizing criteria that can be employed in the evaluation of the spectral quality of fused satellite images.

The fused satellite images in more spectral and high quality can be given by the method wavelet-based image fusion. The Brovey, HIS and PCA methods are having high spatial information then the wavelets of fused images. Fused image has the spatial information which is an important factor as the spectral information in many remote sensing applications. In other words, it is necessary to develop an advanced image fusion method so that fused images have the same spectral resolution as multispectral images and the same spatial resolution as a panchromatic image with minimal artifacts

Recently, other multi-scale systems have been developed, including ridgelets and curvelets. These approaches are very different from wavelet similar systems. Basis elements are taken by transformation like Curvelets and other one ridgelets, which exhibit more large directional sensitivity and are highly anisotropic. The curvelet transform represents edges better than wavelets, and for the multiscale edge enhancement curvelet is suited. A new image fusion method based on a curvelet transforms. The fused image using the curvelet-based image fusion method yields almost the same detail as the original panchromatic image, because curvelets represent edges better than wavelets.

It also gives the same color as the original multispectral images, because in our algorithm we use the wavelet-based image fusion method. As such, this new method is an optimum method for image fusion. In this study we develop a new approach for

fusing Lansat ETM+ panchromatic and multispectral images [140 and 17] based on the curvelet transform. It also gives the same color as the original multispectral images, because in our algorithm we use the wavelet-based image fusion method.
As such, this new method is an optimum method for image fusion. In this study we develop a new approach for fusing Lansat ETM+ panchromatic and multispectral images [141 and 142] based on the curvelet transform.

4.4 From Classical Wavelets To Curvelets

The Discrete Wavelet Transformation has established an impressive reputation as a tool for mathematical analysis and also processing of signal. It has the disadvantage of poor directionality, which has undermined its usage in many applications. In recent years directional wavelets has been made in the development of significant progress. One way for directional selectivity to improve is the complex wavelet transform. Figure 4.E shows the example of discrete wavelet transform.

However, widely in the past has not been used the complex wavelet transform, by using reconstruction properties and good filter characteristics it is more difficult to design complex wavelets.

One popular technique is the dual-tree complex wavelet transform (DT CWT) proposed by Kingsbury [143 and 144], which added (almost) perfect reconstruction to the other attractive properties of complex wavelets, six directional selectivity's, limited redundancy and efficient O(N) computation.

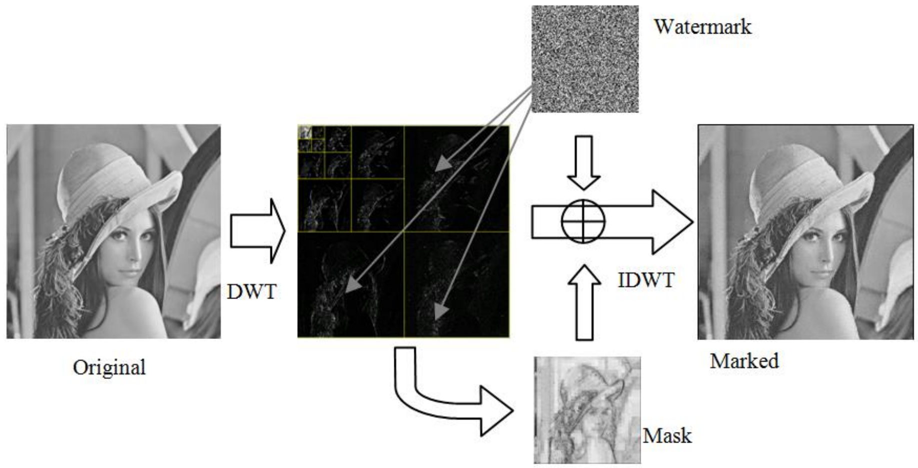


Figure 4.E Phases of Discrete Wavelet Transform

The 2-D complex wavelets are essentially constructed by using tensor-product one-dimensional (1-D) wavelets. The directional selectivity provided by complex wavelets (six directions) is much better than that obtained by the classical DWTs , but complex wavelets is still limited.

In 1999, Candès and Donoho [145] proposed a transformation called ridgelet transform and it was also called an anisotropic geometric wavelet transform. The ridgelet transform is optimal at representing straight-line singularities.

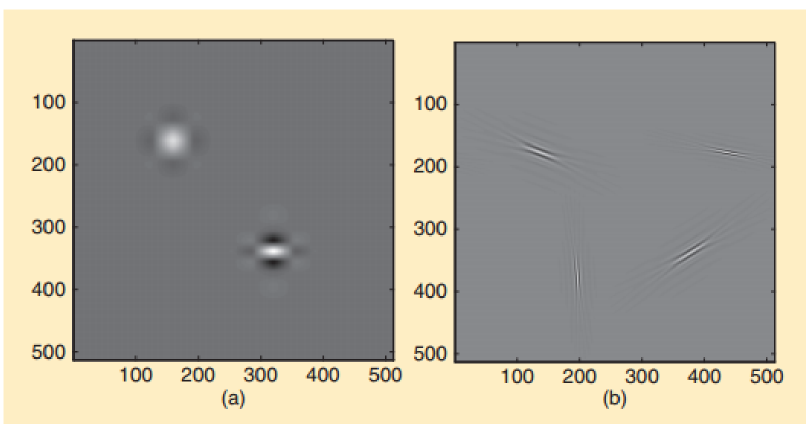


Figure 4.F (a) scales of Wavelets (b) scales of Curvelets

The elements of above figure 4.F (a) wavelets and (b) curvelets on various number of scales, directions, and translations in the spatial domain. Note that the tensor-product are not strictly isotropic in 2-D wavelets but prefer axes directions.

In real applications the global straight-line singularities are rarely observed. To identify and measure local line or curve singularities, a best idea is to consider a partition of the image, and then to apply the ridgelet transform to the obtained sub images. This block ridgelet-based transform, which is named curvelet transform, was first proposed by Candes and Donoho in 2000.

Apart from the blocking effects, however, the application of this so-called first-generation curvelet transform is limited because the geometry of ridgelets is itself unclear, as they are not true ridge functions in digital images. Later, a considerably simpler second-generation curvelet transform based on a frequency partition technique.

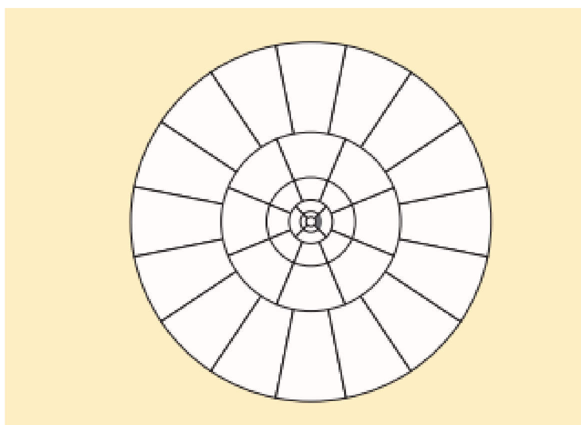
In this section, we discussed about the construction of a discrete curvelets frame. The structure of 1-D wavelets being well localized in frequency domain, we consider the question how these ideas can suitably be transferred to construct a curvelets frame that is an (almost) rotation-invariant function frame in two dimensions. Finally, summarize the properties of the obtained curvelets elements.

4.5 How To Transfer This Idea To The Curvelets Construction

To transfer this construction principle to the 2-D case for image analysis and incorporate certain rotation invariance. To construct a frame, f, this time using translations, dilations, and rotations of F. Following the considerations in the 1-D case, the elements of the curvelets family should now provide a tiling of the 2-D frequency space. Therefore the curvelets construction is now based on the following two main ideas.

1) Consider polar coordinates in frequency domain.

2) Construct curvelets elements being locally supported near wedges, where the number of wedges at the scale, i.e., it doubles in each second circular ring.



4.G Tiling of the frequency domain into wedges for curvelets construction

We use suitable window functions W and V(Nj) , and where a rotation of j, 0, 0 corresponds to the translation of a 2p-periodic window function V(Nj). The index Nj indicates the number of wedges in the circular ring at scale 22j. To construct a (dilated) basic curvelets [98] with compact support near a "basic wedge" the two windows W and V (Nj) need to have compact support. The idea is to take W(r) similarly as in the 1-D case, to cover the interval 10, `2 with dilated curvelets, and to take V (Nj) such that a covering in each circular ring is ensured by translations of V

(Nj). Here, we cannot take the complete Meyer wavelet to determine W, but only the part that is supported.

4.6 Recent Curvelets based Applications

In this section, we shall review applications of the curvelets in image processing, seismic exploration, fluid mechanics, solving of PDEs, and compressed sensing, to show their potential as an alternative to wavelet transforms in some scenarios.

A) Image Processing

In imaging science, image processing can be done by using mathematical operations and any form of signal processing, for that the image will the input, such as a photograph or video frame. An image or set characteristics will the output of the image processing and some parameters also related to the image. In image processing an image can be treated as a two-dimensional signal and applying techniques to image processing that are standard signal-processing.

Image processing sometimes refers to other processing like digital image processing [105], and also optical and analog image processing also are possible. This article is about general techniques that apply to all of them. The acquisition of images (producing the input image in the first place) is referred to as imaging.

Image processing is mostly related to one computer graphics and second computer vision. In computer graphics, by using physical models of objects an images will made and some environments, and lighting will be used instead of being acquired from natural scenes, as in most animated movies. An image or set characteristics will the output of the image processing and some parameters also related to the image. In image processing an image can be treated as a two-dimensional signal and applying techniques to image processing that are standard signal-processing.

On the other hand Computer vision is considered as high-level image processing out of which a machine/computer/software intends to decipher the physical contents of an image or a sequence of images (e.g., videos or 3D full-body magnetic resonance scans). In computer graphics, by using physical models of objects an images will made and some environments, and lighting will be used instead of being acquired from natural scenes, as in most animated movies. An image or set characteristics will the output of the image processing and some parameters also related to the image. In image processing an image can be treated as a two-dimensional signal and applying techniques.

In modern sciences and technologies, due to the ever growing importance of scientific visualization images also gain much broader scopes (of often large-scale complex scientific/experimental data). Examples include microarray data in genetic research, or real-time multi-asset portfolio trading in finance.

B) Fluid Mechanics

Fluid mechanics is the branch of physics which the study belongs to fluids (liquids, gases, and plasmas) and the forces on them.

Fluid mechanics can be classified into fluid statics, which involves the study of fluids at rest; and second fluid dynamics, which involves the study of the effect of forces on fluid motion.

It is a branch of continuum mechanics, a subject which models matter without using the information that it is made out of atoms; that is, it models matter from a macroscopic viewpoint rather than from microscopic. Fluid mechanics, especially fluid dynamics, is an active field of research with many problems that are partly or wholly unsolved. Fluid mechanics can be mathematically complex, and can best be solved by numerical methods [121], typically using computers. A modern discipline, called computational fluid dynamics (CFD), is devoted to this approach to solving fluid mechanics problems. Particle image velocimetry, an experimental method for visualizing and analyzing fluid flow, also takes advantage of the highly visual nature of fluid flow.

Recently, the curvelets have been applied to study the nonlocal geometry of eddy structures and the extraction of the coherent vortex field in turbulent flows. Curvelets start to influence the field of turbulence analysis and have the potential to upstage the wavelet representation of turbulent flows addressed. The multi scale geometric property, implemented by means of curvelets, provides the framework for studying the evolution of the structures associated to the main ranges of scales defined in Fourier space, while keeping the localization in physical space that enables a geometrical study of such structures.

Such a geometrical characterization can provide a better understanding of cascade mechanics and dissipation-range dynamics. Moreover, curvelets have the potential to contribute to the development of structure-based models of turbulence fine scales [65], sub grid scale models for large-eddy simulation [79], and simulation methods based on prior wavelet transforms.

C) Partial differential equation (PDE)

In mathematics, a partial differential equation (PDE) is a differential equation that contains unknown multivariable functions and their partial derivatives. (This is in contrast to ordinary differential equations (ODEs), which deal with functions of a single variable and their derivatives.) PDEs are used to formulate problems involving functions of several variables, and are either solved by hand, or used to create a relevant computer model.

PDEs can be used to describe a wide variety of phenomena such as sound, heat, electrostatics, electrodynamics, fluid flow, elasticity [63], or quantum mechanics. These seemingly distinct physical phenomena can be formalized similarly in terms of PDEs. Just as ordinary differential equations often model one-dimensional dynamical systems, partial differential equations often model multi-dimensional systems. PDEs find their generalization in stochastic partial differential equations.

4.7 Ridgelet Transformation

Definition: An answer to the weakness of the separable wavelet transform is Ridgelet and the Curvelets transforms in sparsely representing what appears to be a simple building atom in an image that is lines, curves and edges. High directional sensitivity and are highly anisotropic are exhibited by the basic elements of ridgelet and the curvelets. Based on the ideas of multiscale analysis and geometry recent geometric image representation was build.

They have had an important success in a wide range of image processing applications including de-noising de-convolution, contrast enhancement, texture analysis, detection, watermarking, and component separation, in painting or blind source separation. Beyond the traditional image processing application the curvelets in diverse proven those are useful. Seismic-imaging, astronomical imaging, scientific computing and analysis are partial differential equations. Another reason for the success of ridgelets and curvelets is the availability of Fast transform algorithms [88] are available to the ridgelet and curvelets is the success. The basic process flow diagram of ridgelet is shown in figure 4.H.

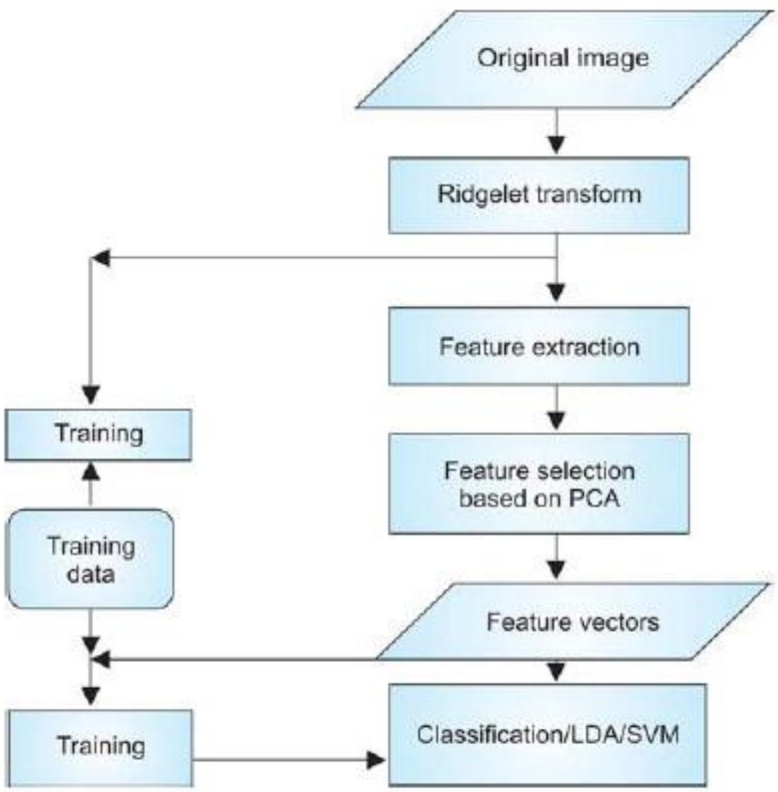


Figure 4.H High level Flow Diagram of Ridgelet Transform

4.8 Sparse Geometrical Image Representation

Despite the wavelet viewpoint success of the classical, it was argued that the traditional wavelets present some strong limitations that question their effectiveness in higher-dimension than 1. Wavelets rely on a dictionary of roughly isotropic elements occurring at all scales and locations, do not describe well highly anisotropic elements, and contain only a fixed number of directional elements, independent of scale.

Following this reasoning, new constructions have been proposed such as the ridgelet and the curvelets. Ridgelets and curvelets are special members of the family of multi-scale orientation-selective transforms [18], which has recently led to a flurry of research activity in the field of computational and applied harmonic analysis. Many other constructions belonging to this family have been investigated in the literature, and go by the name contourlets, directionlets, bandlets, grouplets, shearlets, dual-tree wavelets and wavelet packets, etc.

Practical images and signals may not be supported in a transform domain on a set of relatively small size (sparse set). Instead, they may only be compressible (nearly sparse) in some transform domain [57].

Hence, with a slight abuse of terminology, that will say that a representation is sparse for an image within a certain class that provides a compact description of such an image as shown in below figure 4.I.

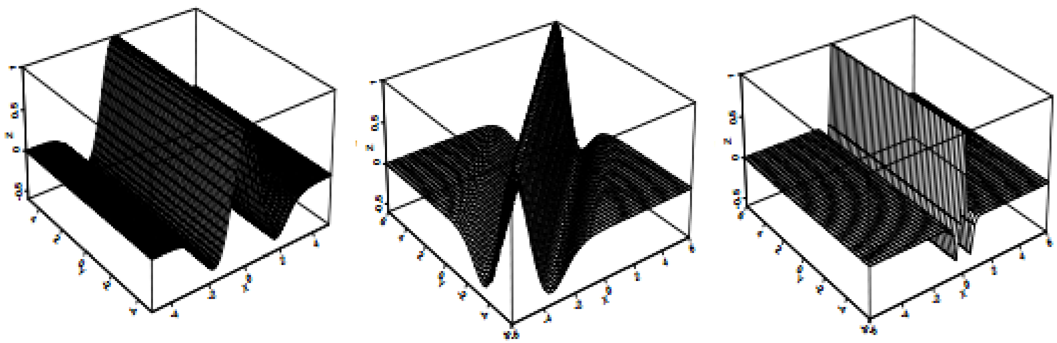


Figure 4.I : Few Ridgelets examples - The second to fourth graphs are obtained after simple geometric manipulations of the first ridgelet, namely rotation, rescaling, and shifting.

A) The Continuous Ridgelet Transform

The two-dimensional continuous ridgelet transform in R^2 can be defined as follows. We pick a smooth univariate function ψ: R → R with sufficient decay and satisfying the admissibility condition

$$\int |\hat{\psi}(\nu)|^2 / |\nu|^2 \, d\nu < \infty, \qquad (1)$$

Which holds if, say, ψ has a vanishing mean $\int \psi(t)dt = 0$. We will suppose a special normalization about ψ so that $\int_0^\infty |\hat{\psi}(\nu)|^2 \nu^{-2} d\nu = 1$.

For each scale a > 0, each position b ∈ R and each orientation θ ∈ [0, 2π), we define the bivariate ridgelet $\Psi_{a, b, \theta}: R^2 \rightarrow R$ by

$$\Psi_{a, b, \theta}(x) = \Psi_{a, b, \theta}(x_1, x_2) = a^{-1/2} \cdot \psi((x_1 \cos\theta + x_2 \sin\theta - b)/a); \qquad (2)$$

A ridgelet is constant along lines $x_1 \cos\theta + x_2 \sin\theta = \text{const}$. Transverse to these ridges it is a wavelet. Figure 4.I depicts few examples of ridgelets. The second to fourth panels are obtained after simple geometric manipulations of the ridgelet (left panel), namely rotation, rescaling, and shifting. Given an integrable bivariate function f(x), we define its ridgelet coefficients by

$$\mathbf{R_f\ (a, b, \theta):=f, \Psi_{a, b, \theta} = \int R^2\ f(x)\ \Psi_{a, b, \theta}\ (x)dx.}$$

4.9 The Recto Polar Ridgelet transform

A fast implementation of the Radon transform can be proposed in the Fourier domain, based on the projection-slice-theorem. First the 2D FFT of the given image is computed. Then the resulting function in the frequency domain is to be used to evaluate the frequency values in a polar grid of rays passing through the origin and spread uniformly in angle. This conversion from Cartesian to Polar grid could be obtained by interpolation, and this process is well known by the name gridding in tomography. Given the polar grid samples [3], the number of rays corresponds to the number of projections, and the number of samples on each ray corresponds to the number of shifts per such angle. Applying one dimensional inverse Fourier transform for each ray, the Radon projections are obtained.

The above described process is known to be inaccurate due to the sensitivity to the interpolation involved. This implies that for a better accuracy, the first 2D-FFT employed should be done with high-redundancy. An alternative solution for the Fourier-based Radon transform exists, where the polar grid is replaced with a pseudo-polar one. The geometry of this new grid is illustrated in below Figure. Concentric circles of linearly growing radius in the polar grid are replaced by concentric squares of linearly growing sides. The rays are spread uniformly not in angle but in slope.

These two changes give a grid vaguely resembling the polar one, but for this grid a direct FFT can be implemented with no interpolation. When applying now 1D-FFT for the rays [6 and 18], we get a variant of the Radon transform, where the projection angles are not spaced uniformly. For the pseudo-polar FFT to be stable, it was shown that it should contain at least twice as many samples, compared to the original image we started with. A by-product of this construction is the fact that the transform is organized as a 2D array with rows containing the projections as a function of the angle. Thus, processing the Radon transform in one axis is easily implemented.

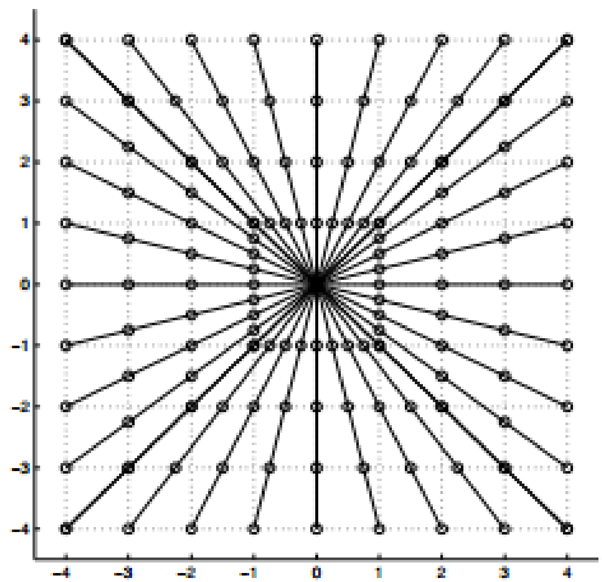


Figure 4.J Pseudo-Polar grid in frequency domain for an n by n image

4.10 The Orthonormal Finite Ridgelet Transform

The orthonormal finite ridgelet transform (OFRT [147]) has been proposed for image compression and filtering. This transform is based on the finite Radon transform and a 1D orthogonal wavelet transform. It is not redundant and reversible. It would have been a great alternative to the previously described ridgelet transform if the OFRT were not based on an awkward definition of a line. In fact, a line in the OFRT is defined algebraically rather that geometrically, and so the points on a ’line’ can be arbitrarily and randomly spread out in the spatial domain.

Below figure shows the back-projection of a ridgelet coefficient by the FFT-based ridgelet transform (left) and by the OFRT (right). It is clear that the back projection of the OFRT is nothing like a ridge function. Because of this specific definition of a line, the threshold of the OFRT coefficients produces strong artifacts.

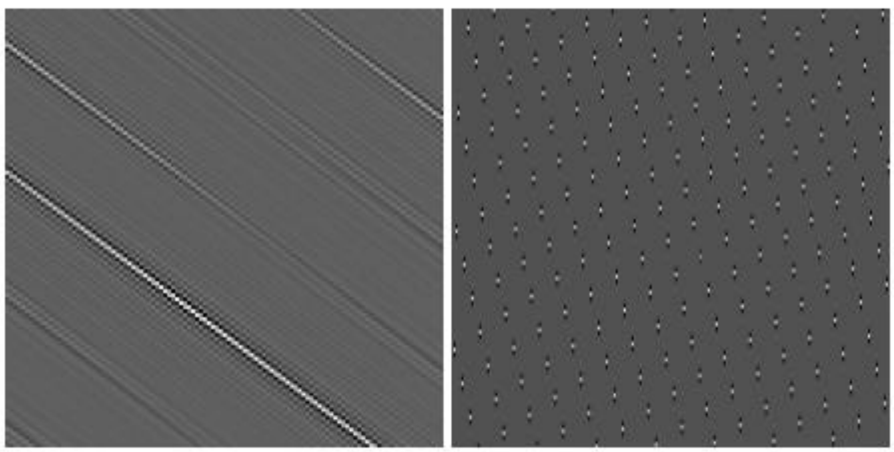


Figure 4.K Example of Orthonormal Finite Ridgelet Transform

The resulting image is not smoothed as one would expect, but rather a noise has been added to the noise-free image as part of the filtering! Finally, the OFRT presents another limitation: the image size must be a prime number. This last point is however not too restrictive, because we generally use a spatial partitioning when de-noising the data, and a prime number block size can be used. The OFRT is interesting from the conceptual point of view, but still requires work before it can be used for real applications such as de-noising.

4.11 Local Ridgelet Transforms

The ridgelet transform is optimal for finding global lines of the size of the image. To detect line segments, a partitioning must be introduced. The image can be decomposed into overlapping blocks of side-length b pixels in such a way that the overlap between two vertically adjacent blocks is a rectangular array of size b by b/2; we use overlap to avoid blocking artifacts.

For an n by n image, we count 2n/b such blocks in each direction, and thus the redundancy factor grows by a factor of 4.

The partitioning introduces redundancy, as a pixel belongs to 4 neighboring blocks. We present two competing strategies to perform the analysis and synthesis:

- The block values are weighted by a spatial window w (analysis) in such a way that the co-addition of all blocks reproduce exactly the original pixel value (synthesis).
- The block values are those of the image pixel values (analysis) but are weighted when the image is reconstructed (synthesis [51]).

The continuous ridgelet transform provides sparse representation of both smooth functions and of perfectly straight lines. Just seen that there are also various discrete ridgelet transforms those expansions with countable discrete collection of generating elements, which correspond either to frames or ortho-bases.

These are seen in schemes that the DRT achieves near-optimal M-term approximation [64] - that is the non-linear approximation of f using the M highest ridgelet coefficients in magnitude - to smooth images with discontinuities along straight lines. In summary, ridgelets provide sparse presentation for piecewise smooth images away from global straight edges.

CHAPTER -5

EXPERIMENTS AND RESULTS

Objectives of this chapter

5.1 Experiments

5.2 Experimental Setup

5.3 Sliced Ridgelet Transform result comparison

A. MRI Scan Image experiment
B. House image experiment
C. Lady image experiment
D. Finger Print image experiment
E. Barbara image experiment

5.4 Experimental Result discussion

5.5 Experimental Result Graph Representation

5.1 Experiments

In this section we discuss about the image de-noising experiments in detail with our proposed sliced ridgelet transform methodology. In these experiments, we simulate noisy images by corrupting the 512 x 512 textured grass images with 10 different realizations of WGN with standard deviation 25. The noisy images are then de-noised with various existing methodologies and our sliced ridgelet transform environment.

We perform our experiments on the well-known images Lena, MRI Scan, and Fingerprint. We get these images from the free software package Wave Lab developed by Donoho et al. at Stanford University. Noisy images with different noise levels are generated by adding Gaussian white noise to the original noise-free images. For comparison, we implement VisuShrink [146], RidgeletShrink [147 and 148], SlicedRidgeletShrink and wiener2 [149 and 150]. VisuShrinkis the universal soft-threshold denoising technique. The wiener2 function is available in the MATLAB Image Processing Toolbox, and we use a 5×5 neighborhood of each pixel in the image for it. The wiener2 function applies a Wiener filter (a type of linear filter) to an image adaptively, tailoring itself to the local image variance.

The experimental results in PSNR are shown is for de-noising Lena image for different image partition block sizes by using ComRidgeletShrink. It can be seen that the partition block size of 32×32 or 64×64 is our best choice as shown in figure 5.A.

For the experiments of image corpus we used the image slicing tool, which is open source software Fiji http://fiji.sc/wiki/index.php/Fiji It's essentially the same as

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Image J, but comes with many pre-installed plugins and can update itself automatically. For all the experiments, we chose q = 2 and N = 2 for ISKR.

In experiments already reported the size of the directional windows was kept constant from a decomposition level to next decomposition level. There are references which recommend reducing the size of the directional estimation windows from a decomposition level to the next decomposition level.

5.2 Experimental Setup

Here we describe the all experimental software's and its relevant plug-ins. These software's also explained in detail here. For this we are using Fiji Software slicing, Sliced Ridgelet framework and other important ones as per the relevance.

We illustrate the output components obtained from the previously described empirical transforms. The tests are made on two different images. The first one is a lady image example containing some flat objects as well as different textures lying at different scales and orientations; this image and its Fourier spectrum are given in the figure 5.A.

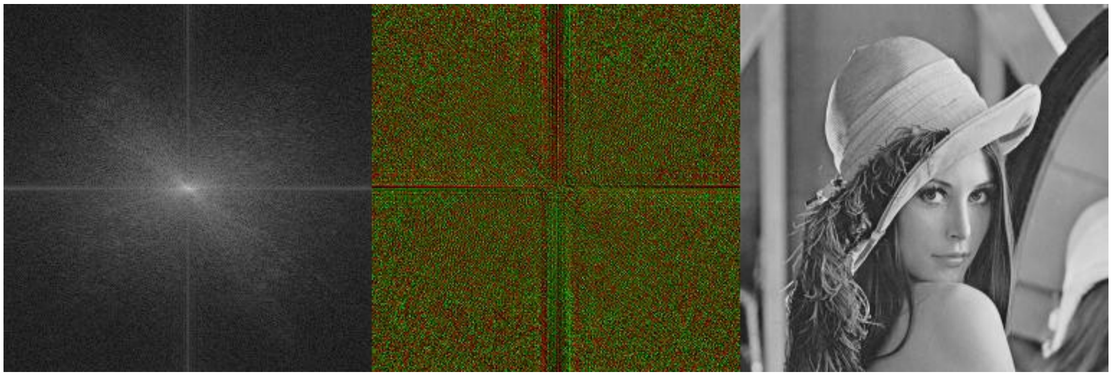

Figure 5. A 2-D Fourier Transform of a lady image

In order to have some intuition on the applicability of the proposed transforms, in this section, we present some de-noising experiments. The used de-noising method consists in three simple steps:

- We perform the transform of a noisy image
- Then we apply a soft threshold on the obtained coefficients
- Finally we perform the inverse transform to get the de-noised image.

This method is not the best de-noising method in the literature but it is sufficient to get some clues on the proposed transforms. The noisy images are built from the toy and Lena images, mentioned in the previous section, on which we add an additive Gaussian noise. The used threshold is given by δ p 2 log Np, where NP is the number of pixels and δ is a tuning parameter, optimized on each experiment to get the best de-noising results. To compare the de-noising efficiency, we compute two different metrics (the reference image is denoted Ir and the de-noised image Id. Here we gave the example for the 3 step approach in figure 5.B.

Figure 5. B Our sliced ridgelet 3-step approach for de-noising.

5.3 Sliced Ridgelet Transform result comparison

A) MRI Scan image experiment: In MRI Scan experiment, for different noise levels and a fixed partition block size of 32×32 pixels. The first column in these tables is the PSNR of the original noisy images, while other columns are the PSNR of the de-noised images by using different donoising methods along with our proposed sliced ridgelet transform and the result is as shown in below figure 5.C.

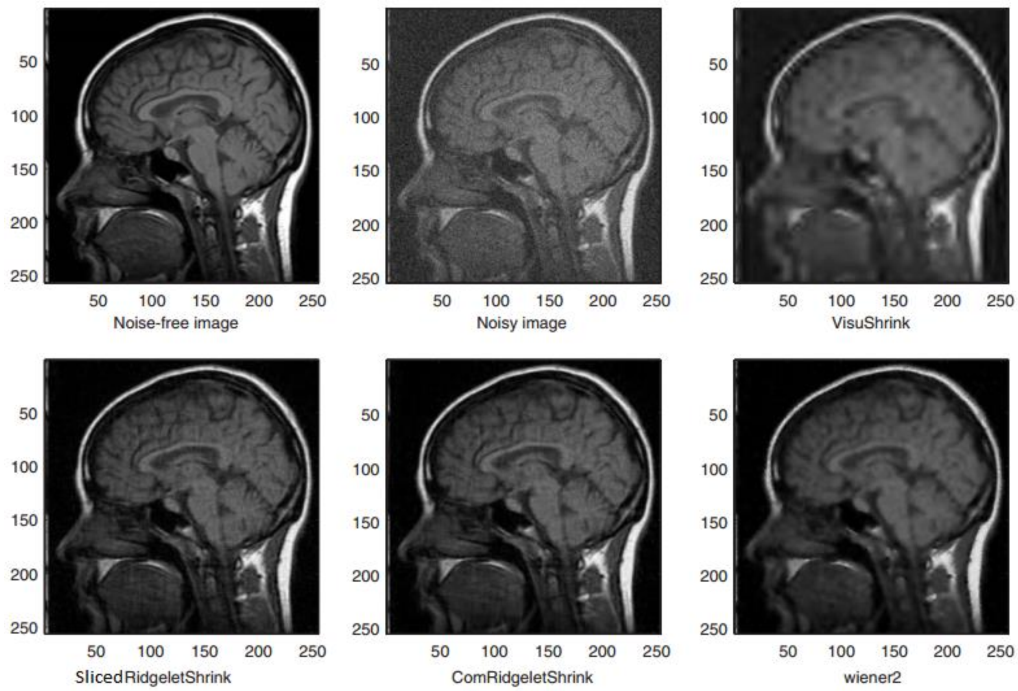

Figure 5. C MRI Scan Experiment with various image de-noising methodologies

From Tables 5.1 and 5.2 we can see that SlicedRidgeletShrink out performs VisuShrink, the ordinary RidgeletShrink, andwiener2for all cases. VisuShrink does not have any donoising power when the noise level is low. Under such a condition, VisuShrink produces even worse results than the original noisy images. However, SlicedRidgeletShrink performs very well in this case. For some case, SlicedRidgeletShrink gives us about 1.30 dB improvements over the ordinary RidgeletShrink.

B) House image experiment: In Home experiment, for different noise levels and a fixed partition block size of32×32 pixels. The first column in these tables is the PSNR of the original noisy images, while other columns are the PSNR [151 and 152] of the de-noised images by using different donoising methods along with our proposed sliced ridgelet transform and the result is as shown in below figure 5.D.

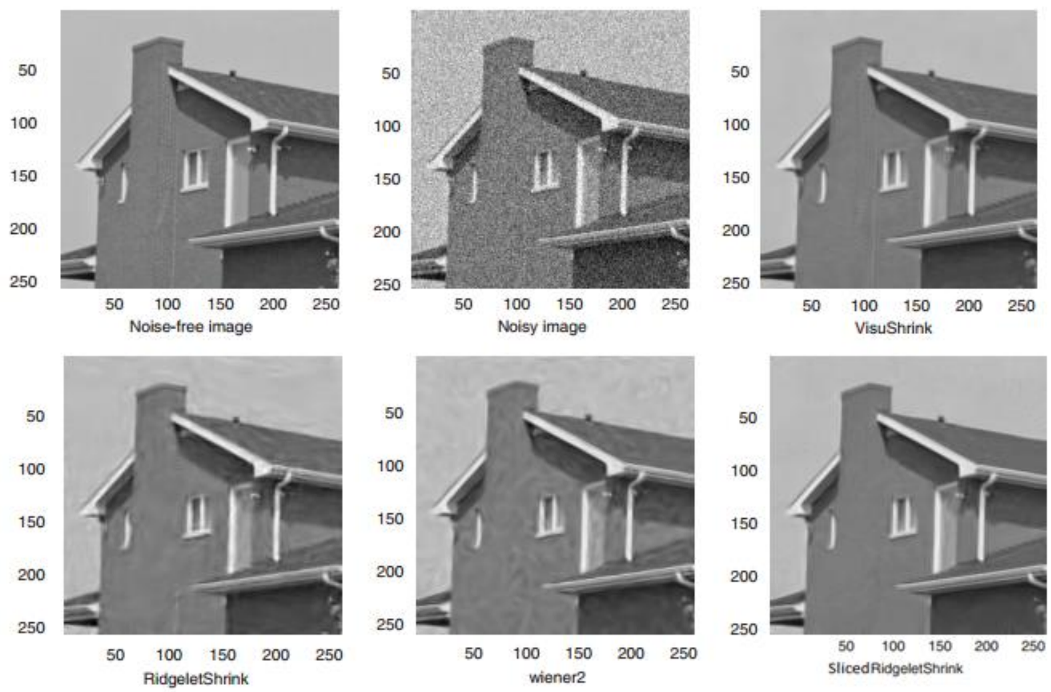

Figure 5. D House Image experiment with various image de-noising methodologies

C) Lady Image experiment: In Lady experiment, for different noise levels and a fixed partition block size of 42×32 pixels. The first column in these tables is the PSNR of the original noisy images, while other columns are the PSNR of the de-noised images by using different donoising methods along with our proposed sliced ridgelet transform and the result is as shown in below figure 5.E.

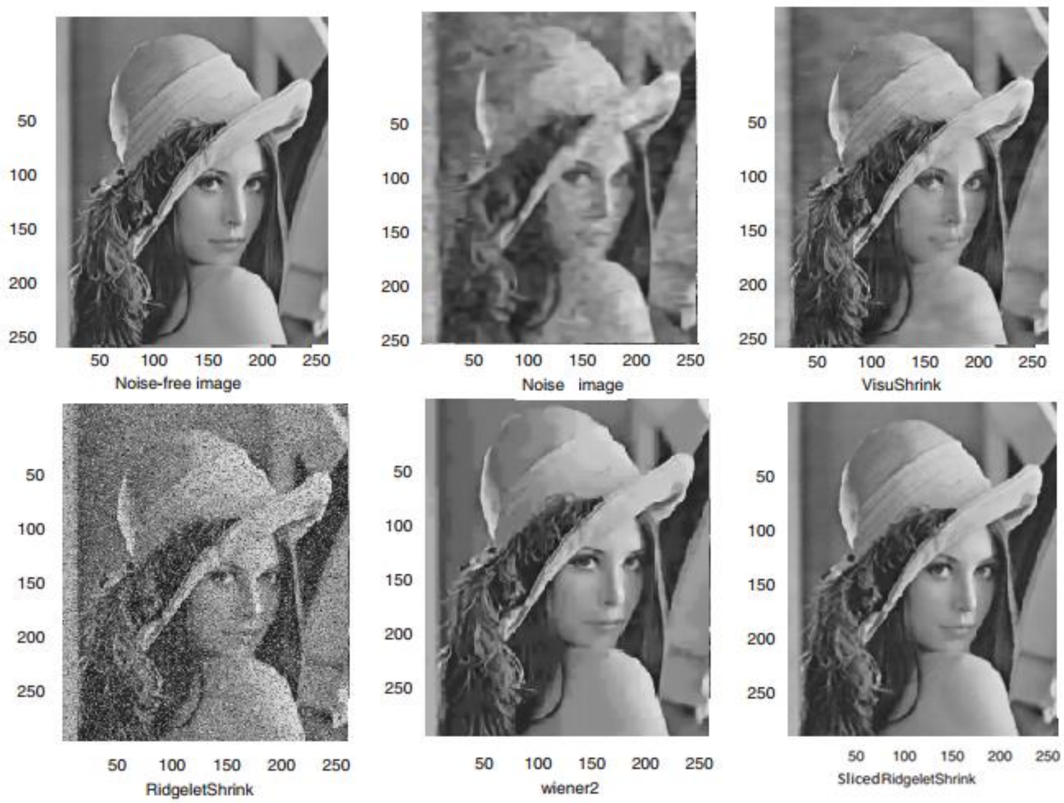

Figure 5. E Lady Image experiment with various image de-noising methodologies

D) Finger Print Image Experiment: In Finger Print experiment, for different noise levels and a fixed partition block size of 42×32 pixels. The first column in these tables is the PSNR of the original noisy images, while other columns are the PSNR of the de-noised images by using different donoising methods along with our proposed sliced ridgelet transform and the result is as shown in below figure 5.F.

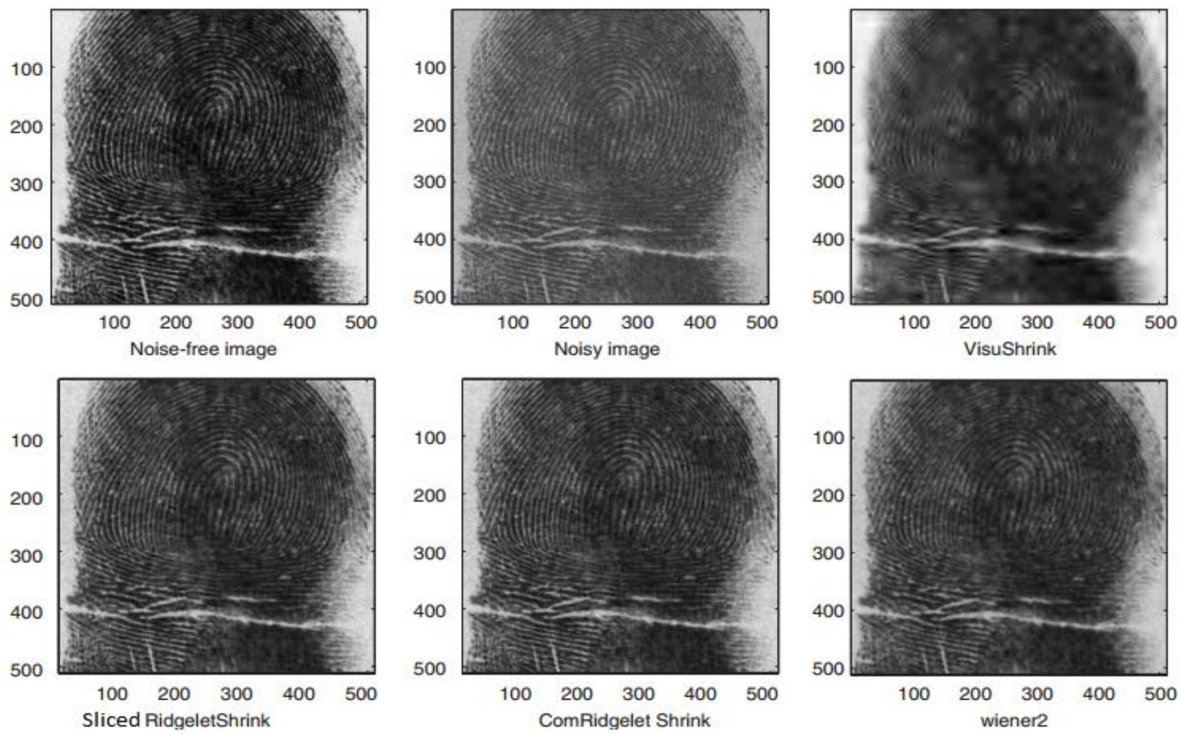

Figure 5. F Lady Image experiment with various image de-noising methodologies

E) Barbara Image Experiment: In Finger Print experiment, for different noise levels and a fixed partition block size of 42×32 pixels.

The first column in these tables is the PSNR of the original noisy images, while other columns are the PSNR of the de-noised images by using different donoising methods along with our proposed sliced ridgelet transform and the result is as shown in below figure 5.G.

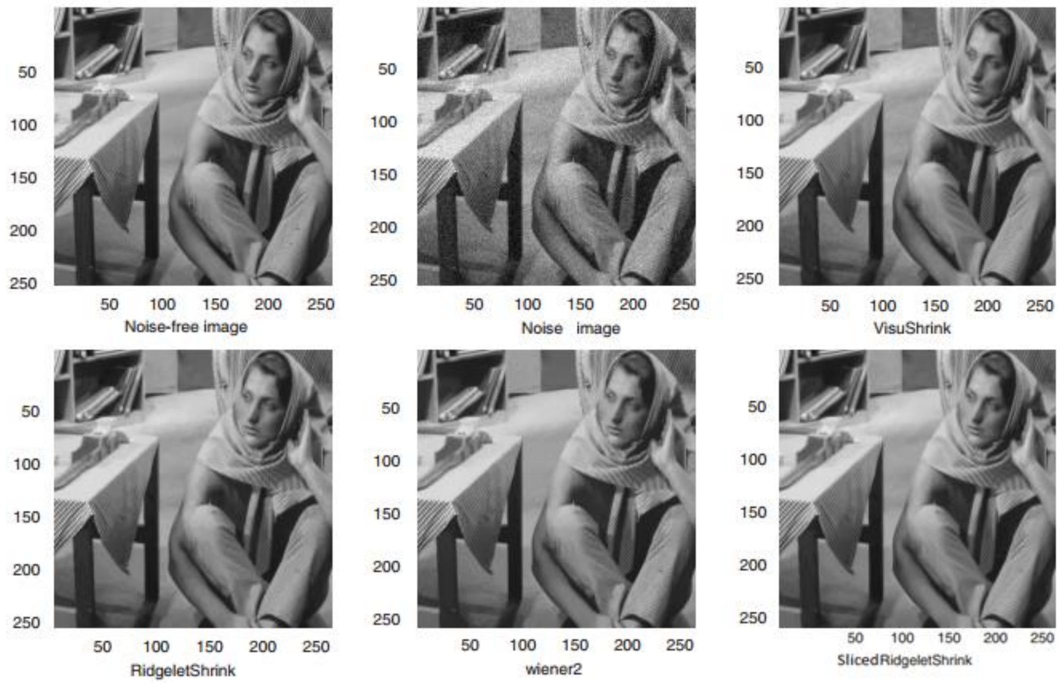

Figure 5. G Barbara Image experiment with various image de-noising methodologies

5.4 Experimental Result Discussion

The complex ridgelet transform can be applied to the entire image or we can partition the image into a number of over lapping squares and we apply the ridgelet transform to each square. We decompose the original n×n image into smoothly overlapping blocks of side length R pixels so that the overlap between two vertically adjacent blocks is a rectangular array of size R/2×Rand the overlap between two horizontally adjacent blocks is a rectangular array of size R×R/2.

In order to get the de-noised complex ridgelet coefficient, we use the average of the four de-noised complex ridgelet coefficients in the current pixel location. This approach is the fastest and most effective way to generate better de-noised images

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Table 5.1 is for de-noising MRI scan image for different image partition block sizes by using SlicedRidgeletShrink. It can be seen that the partition block size of 32×32or 64×64 is our best choice.

In Table 5.1 we quantify the performances for a variety of bench mark images, across different noise levels. The results there show that, in terms of PSNR, visuShrink [66] and the no-reference quality metric Q [67], our method is quite comparable to VisuShrink [49] and Wenier[43]. While Weiner is quite fast, the algorithm's high performance has not been well-justified on theoretical grounds as of yet.

On the other hand, NLSM can be quite complicated in terms of the steps involved. In contrast, our method is well-motivated, and provides a statistical explanation for its performance. Moreover, when "oracle" filter parameters are used, our method generally improves on the state-of-the-art performance, especially for strong noise cases. This shows the true potential of our de-noising approach, given improved estimates of the parameters.

Noisy image	VisuShrink	RidgeletShrink	SlicedRidgeletShrink	wiener2
34.12	29.49	36.67	**37.19**	30.96
28.10	26.31	32.51	**33.13**	30.09
24.58	24.77	30.23	**30.79**	29.04
22.08	23.85	28.63	**29.21**	28.01
20.14	23.24	27.39	**28.00**	27.07
18.56	22.83	26.39	**27.03**	26.22

Table 5.1 MRI Scan Comparison with various donoising techniques

Noisy image	VisuShrink	RidgeletShrink	SlicedRidgeletShrink	wiener2
34.12	30.07	37.41	**38.17**	31.23
28.10	26.81	33.31	**34.09**	30.46
24.58	25.12	30.98	**31.76**	29.48
22.08	24.04	29.33	**30.13**	28.47
20.14	23.28	28.06	**28.89**	27.52
18.56	22.70	27.05	**27.87**	26.64

Table 5.2 Home Image Comparison with various donoising techniques

In Table 5.3 we will see that this agrees with the conclusions of our performance bounds that expect greater improvement in performance for the class of smoother images. Images containing more semi-stochastic texture typically exhibit lower levels of patch redundancy. For such images, Ridgelet Shrink typically does a better job of de-noising. However, even in such cases, our de-noising results are visually comparable to the state-of-the-art, as shown in Fig. 5.3 where we compare our (sliced ridgelet) results to VisuShrink [43] and RidgeletShrink [49] for some fairly textured regions of different images.

Noisy image	VisuShrink	RidgeletShrink	SlicedRidgeletShrink	wiener2
34.14	28.46	35.73	**36.31**	29.37
28.12	25.72	32.01	**32.58**	28.85
24.59	24.41	29.98	**30.54**	28.21
22.09	23.67	28.55	**29.13**	27.55
20.16	23.21	27.42	**28.04**	26.91
18.57	22.90	26.49	**27.16**	26.26

Table 5.3 Barbara Image Comparison with various donoising techniques

We point out here that the parameters used for our method are kept fixed across all noise levels and images. For all our experiments, we use a patch size of n = 11 x 11, with the number of clusters K set to 15. The smoothing parameter, which controls the amount of de-noising, is also kept fixed at $h^2 = 1.75\sigma^2 n$.

In general, these parameters can be tuned on a per image basis, manually or using some no-reference image quality measure. In our opinion, such tunable parameters make a method less practical. Results presented in here, thus, use the fixed parameter settings mentioned above.

However, for highly textured images (e.g. boat and stream images), the noise variance tends to be over-estimated, when considering strong noise ($\sigma = 25$). This results in slightly over-smoothened de-noised images. For such cases, we provided our algorithm with a lower noise variance.

In terms of visual quality, our method is comparable to VisuShrink and Weiner2, even outperforming them in many cases where images exhibit higher levels of redundancy. This can be observed in Fig. 5.F where our result is more visually pleasing when compared to VisuShrink and Weiner2 both of which produce more artifacts in the smooth floor and face regions. As with the quantitative measures, the visual quality is greatly improved when oracle parameters are used.

This improvement is more pronounced for the strong noise cases and for images containing finer details where parameter estimation is more error prone.

5.5 Experimental result graph representation

From fig. 5.H to 5.K where we compare the de-noising performance for various methods for the synthetically generated stripes image containing multiple exact replicas of each line singularity.

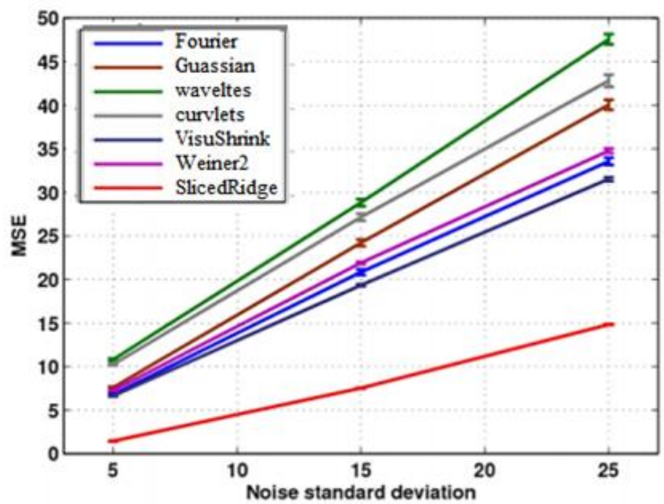

Figure 5. H MRI Scan Image donoising comparison

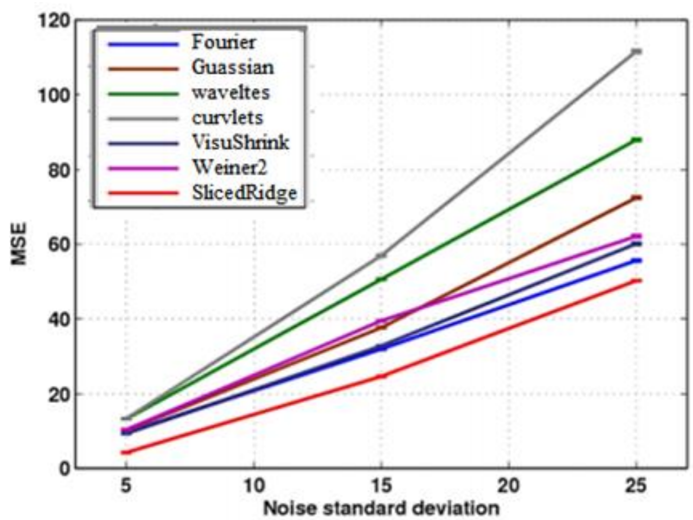

Figure 5.I Lady Scan Image donoising comparison

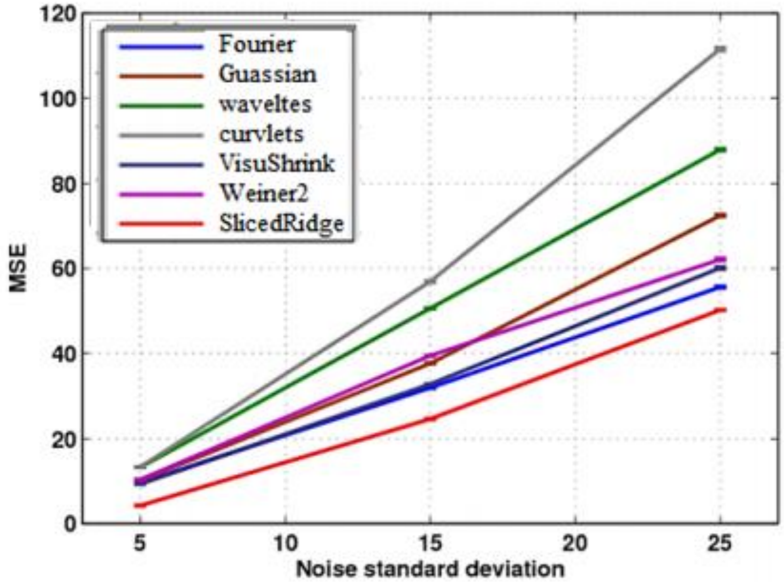

Figure 5. J House Image donoising comparison

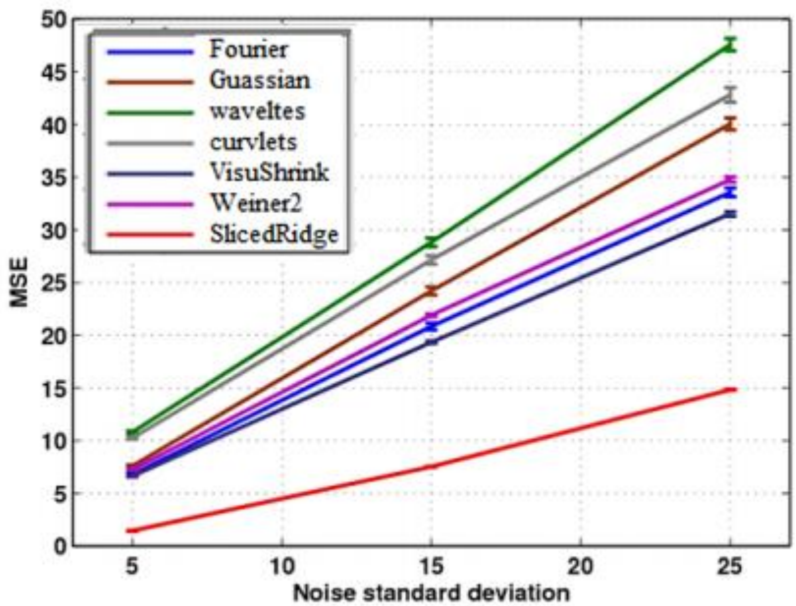

Figure 5. K Barbara Image donoising comparison

For strong noise, the non-local methods, namely VisuShrink[49], Weiner2 [43] and Guassian [68, 69], Sliced Rigelet clearly outperform the local approaches. High levels of redundancy as well as low patch complexity result in our bounds predicting a very small lower bound even for quite strong noise levels.

On the other hand, images that contain mostly semi-stochastic texture demonstrate high variability among its patches, with each patch itself being structurally quite complex. The bound for this particular image is much higher in comparison to the simpler stripes image. Low redundancy [153] levels also translate to indistinguishable performance difference between the local and non-local methods, as shown in Fig. 5.A.

Interestingly, for this image, the predicted bound is very close to the MSE obtained by the methods, implying almost no room for performance improvement. A similar observation is made for the somewhat less random cloth image as well, although in this case some modest improvement is still possible.

Intuitively, we can expect lower redundancy levels for more complex patches (e.g., patches in corner and texture regions), whereas more similar patches can be expected for smoother patches. This leads to better denoising for images lacking much texture. Our bound formulation, being data dependent, is in keeping with this intuition, as illustrated in Fig. 5.D&E. As expected, the bounds for the house image are quite lower than those for the Barbara image. This relative denoising difficulty is also seen in the performance of the methods to which we have compared.

Although rich in texture, a majority of the complex patches follow definite patterns, thus providing higher redundancy levels than the texture regions of most other images. The presence of more similar patches is advantageous to the non-local methods. Not surprisingly, these methods achieve much better performance than the local denoising filters, especially when the corrupting noise is strong(see Fig. 5.F).

That the non-local methods exploit such redundancies efficiently is demonstrated by the fact that the performance of such methods is comparable to the bounds. Observe that the room for improvement is much smaller than the smoother house image indicating the possibility of better redundancy exploitation, but more than the highly textured grass image where very few similar patches are observed.

Comparing performances of the state-of-the-art methods [154] to the bounds allows us to gauge the room for improvement in denoising performance of any given image. As a result, the bounds for natural images are usually much higher. The room for improvement for natural images can also be seen to be much lower than those for the synthetic images used in our study. Even for these natural images, the plots at low SNRs can be segregated into two regions.

From the above discussion, it becomes apparent that image denoising as a problem is not dead – yet. This is particularly true for the class of smoother images containing sufficiently large number of repeating patterns. On the surface, this may appear to be in direct contradiction to the observations in [76] where Levin and Nadler compared the bounds to the best denoising methods and concluded that the performance of current non-parametric approaches cannot be improved upon, unless considerably larger patches are used.

CHAPTER-6

CONCLUSION AND FUTURE WORK

In this paper, we study image de-noising by using sliced ridgelets. It tries to remove the Gaussian white noise presented in the noisy images and also alleviates the limitations of wavelet and general ridgelet problems. Recent trends in ridgelet transforms proven that they are better than wavelet transforms to reduce the noise in images. This thesis concentrates on improvising the features of ridgelet transform to perform well than what it stands. As per our concern there is a wide research area and scope is still waiting for research concentration in ridigelet transforms.

Although several de-noising techniques were introduce by previous research scholars, Image processing is still suffering from the noise problem and results accuracy is affecting due to the blur or noise data of an image. Various image noise problems were existed in processing standard, orthogonal and limited size images are: additive white noise, Thermal noise, Fixed Pattern noise, Quantization noise, Dark current noise etc. Popular de-noising techniques were proposed in the area of image processing recently like wavelets, curvlets and some other edge based technologies, they have problem with complexity in finding approximate shift invariant property of the dual-tree and high directional sensitivity etc.

In order to overcome the above mentioned problems we are designing and implementing an integrated, comprehensive and scalable solution is sliced ridgelet transformation for image de-noising.

This Research work introduces sliced ridgelet transform for image de-noising, and to achieve the scalability and accuracy and in a reliable manner of image processing. Image de-noising that is based on ridgelets computed in a localized manner and that is computationally less intensive than curvelets, but similar donoising performance. Sliced ridgelet transform’s ridge function is segregated to multiple slices with constant length. Single-dimension wavelet transforms are used to compute the angle values of each slice in sliced ridgelet transform. Ridgelet co-efficient are obtained for the base threshold calculation to implement the accurate de-noising.

This new method for image de-noising technique is based on two operations: one is the redundant directional wavelet transform based on the radon transform, and threshold designing of the ridgelet coefficient.

This research work compares the accuracy and scalability of image de-noising with other popular approaches like wavelets, curvlets and some other inter-relevant technologies. We test our new denoising method with several standard images with Gaussian white noise added to the images. A very simple hard thresholding of the complex ridgelet coefficients is used. Experimental results show that complex ridgelets give better denoising results than VisuShrink, wiener2, and the ordinary ridgelets under all experiments. We suggest that ComRidgeletShrinkbe used for practical image donoising applications. Experimental results are proven that the sliced ridgelet approach is having the better performance than the other popular techniques.

Future work: Future work will be done by considering sliced ridgelets in curvelets image de-noising. Also, complexridgelets could be applied to extract invariant features for pattern recognition.

The computational cost of the sliced ridgelet transform is bit higher than that of ridgelets, especially in terms of 3D problems. We set the goal of reducing the computational cost of sliced ridgelets than general ridgelets is the another area of future research.

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Appendix-A

In this section we discuss about the MATLAB software and its implementation in detail.

The Matlab and other mathematical computation tools are computer programs that combine computation and visualization power that makes them particularly useful tools for engineers. Matlab is both a computer programming language and a software environment for using that language effectively.

The name Matlab stands for Matrix laboratory, because the system was designed to make matrix computations particularly easy. Don't worry if don't know what a matrix is, as this will be explained later. The Matlab environment allows the user to manage variables, import and export data, perform calculations, generate plots, and develop and manage files for use with Matlab.

The Matlab environment is an interactive environment:

- ✓ Single-line commands can be entered and executed, the results displayed and observed, and then a second command can be executed that interacts with results from the first command that remain in memory. This means that you can type commands at the Matlab prompt and get answers immediately, which is very useful for simple problems.
- ✓ Matlab is a executable program, developed in a high level language, which

interprets user commands.

- ✓ Portions of the Matlab program execute in response to the user input, results are displayed, and the program waits for additional user input.
- ✓ When a command is entered that doesn't meet the command rules, an error message is displayed. The corrected command can then be entered. • Use of this environment doesn't require the compile-link/load-execution process described above for high-level languages.

While this interactive, line-by-line execution of Matlab commands is convenient for simple computational tasks, a process of preparation and execution of programs called scripts is employed for more complicated computational tasks:

A script is list of Matlab commands, prepared with a text editor.

- ➢ Matlab executes a script by reading a command from the script file, executing it, and then repeating the process on the next command in the script file.
- ➢ Errors in the syntax of a command are detected when Matlab attempts to execute the command. A syntax error message is displayed and execution of the script is halted.
- ➢ When syntax errors are encountered, the user must edit the script file to correct the error and then direct Matlab to execute the script again.
- ➢ The script may execute without syntax errors, but produce incorrect results when

a logic error has been made in writing the script, which also requires that the script be edited and execution re-initiated.

- Script preparation and debugging is thus similar to the compile-link/load-execution process required for in the development of programs in a high-level language.

Computing Terminology

Definitions of MATLAB computing terms:

Command: A user-written statement in a computer language that provides instructions to the computer.

Variable: The name given to a quantity that can assume a value,.

Default: The action taken or value chosen if none has been specified.

Toggle: To change the value of a variable that can have one of two states or values. For example, if a variable may be “on” or “off” and the current value is “on,” to toggle would change the value to “off.”

Arguments: The values provided as inputs to a command.

Returns: The results provided by the computer in response to a command.

Execute: To run a program or carry out the instructions specified in a command.

Display: Provide a listing of text information on the computer monitor or screen.

Echo: To display commands or other input typed by the user.

Print: To output information on a computer printer (often confused with "display" in the textbook).

Matlab Technical Computing Environment

Matlab provides a technical computing environment designed to support the implementation of computational tasks. Briefly, Matlab is an interactive computing environment that enables numerical computation and data visualization.
Matlab has hundreds of built-in functions and can be used to solve problems ranging from the very simple to the sophisticated and complex. Whether you want to do some simple numerical or statistical calculations, some complex statistics, solve simultaneous equations, make a graph, or run and entire simulation program, Matlab can be an effective tool.

Matlab has proven to be extraordinarily versatile and capable in its ability to help solve problems in applied math, physics, chemistry, engineering, finance – almost any application area that deals with complex numerical calculations.

Running Matlab

Unix: From a terminal window, type matlab, followed by the Enter key

Win 8: double-click on the Matlab icon or select Matlab from Start/Programs

Display Windows

- ✶ Command window Enter commands and data, display results Prompt >> or EDU>> 14
- ✶ Graphics (Figure) window Display plots and graphs Created in response to graphics commands
- ✶ M-file editor/debugger window Create and edit scripts of commands called M-files

When you begin Matlab, the command window will be the active window. As commands are executed, appropriate windows will automatically appear; you can activate a window by clicking the mouse in it.

Getting Help

help – On-line help, display text at command line

help, by itself, lists all help topics

help topic provides help for the specified topic

help command provides help for the specified command

help help provides information on use of the help command

helpwin – On-line help, separate window for navigation.

helpdesk – Comprehensive hypertext documentation and troubleshooting

demo – Run demonstrations

intro – Interactive introduction to Matlab

Scalar Mathematics:

Scalar mathematics involves operations on single-valued variables. Matlab provides support for scalar mathematics similar to that provided by a calculator. For more information, type help ops. The most basic Matlab command is the mathematical expression, which has the following properties:

- Mathematical construct that has a value or set of values.
- Constructed from numbers, operators, and variables.
- Value of an expression found by typing the expression and pressing

Variables and Assignment Statements

Variable names can be assigned to represent numerical values in Matlab. The rules for these variable names are:

- Must start with a letter
- May consist only of the letters a-z, digits 0-9, and the underscore character (_)

- May be as long as you would like, but Matlab only recognizes the first 31 characters
- Is case sensitive: items, Items, it Ems, and ITEMS are all different variable names

Assignment statement:

Matlab command of the form:

- variable = number
- variable = expression

When a command of this form is executed, the expression is evaluated, producing a number that is assigned to the variable. The variable name and its value are displayed. If a variable name is not specified, Matlab will assign the result to the default variable.

Matlab workspace: Variables created in the Command window are said to reside in the Matlab workspace or Base workspace. The workspace retains the values of these variables, allowing them to be used in subsequent expressions.

Special variables:

- ans: default variable name

- pi: ratio of circle circumference to its diameter, $\pi = 3.1415926...$
- eps: smallest amount by which two numbers can differ
- inf or Inf : infinity, e.g. 1/0
- nan or NaN : not-a-number, e.g. 0/0
- date: current date in a character string format, such as 19-Mar-1998.
- flops: count of floating-point operations.

Commands involving variables:

- who: lists the names of defined variables
- whos: lists the names and sizes of defined variables
- clear: clears all variables, resets default values of special variables
- clear var: clears variable var
- clc: clears the command window, homes the cursor (moves the prompt to the top line), but does not affect variables.
- clf: clears the current figure and thus clears the graph window.
- more on: enables paging of the output in the command window.
- more off: disables paging of the output in the command window

Redefining variables A variable may be redefined simply by executing a new assignment statement involving the variable. Note that previously issued commands involving the redefined variable won't be automatically reevaluated.

Command reuse and editing

- Commands can be reused and edited using the following operations:
- Press the up arrow cursor key (↑) to scrolls backward through previous commands. Press Enter to execute the selected command.
- The down arrow cursor key (↓) scrolls forward through commands
- The left (←) and right arrow (→) cursor keys move within a command at the Matlab prompt, allowing the command to be edited.
- The mouse can also be used to reposition the command cursor, by positioning the mouse cursor and pressing the left mouse button.
- Other standard editing keys, such as delete Del , backspace BkSp , home , and end , perform their commonly assigned tasks.
- Once a scrolled or edited command is acceptable, pressing Enter with the cursor any where in the command tells Matlab to process it.
- Escape key Esc erases the current command at the prompt.

Windows copy and paste operations:

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Copy: Highlight a command to be copied by placing the mouse cursor at the beginning of the text to be highlighted, press the left mouse button, and drag the mouse cursor through the text, releasing the mouse button when you reach the end of the text to be copied. The selected, or highlighted, text will appear as white text on black background instead of the reverse. In Unix, the highlighted text is automatically copied (stored internally). In MS Windows, the highlighted text is copied by pulling down the Edit menu and selecting Copy (or typing Ctrl+C).

Paste: To paste the copied text in Unix, move the mouse cursor to the desired location, press the middle mouse button, and the text will be pasted into the window. In MS Windows, reposition the cursor, pull down the Edit menu and select Paste (or type Ctrl+V).

Punctuation and Comments

- Semicolon (;) at the end of a command suppresses the display of the result 23
- Commas and semicolons can be used to place multiple commands on one line, with commas producing display of results, semicolons suppressing
- Percent sign (%) begins a comment, with all text up to the next line ignored by Matlab

- Three periods (...) at the end of a command indicates that the command continues on the next line.
- A continuation cannot be given in the middle of a variable name.

Example Program

```
>> screws = 36

screws =

36

>> items

items =

90

>> items = screws + bolts + rivets

items =

94

>> screws=32, bolts=18; rivets=40; % multiple commands

screws =

32

>> items = screws + bolts + rivets;

>> cost = screws*0.12 + bolts*0.18 + rivets*0.08;

>> average_cost = cost/... % command continuation

items

average_cost =

0.1142
```

Appendix- B

LIST OF PAPERS PUBLISHED IN INTERNATIONAL JOURNALS

1. IOSR Journal of Computer Engineering (IOSR-JCE) e-ISSN: 2278-0661, p- ISSN: 2278-8727Volume 14, Issue 1 (Sep. - Oct. 2013), PP 17-21, www.iosrjournals.org. - SLICED RIDGELET TRANSFORM FOR IMAGE DENOISING. Ip: 4.6

2. International journal of engineering sciences & research technology (I J E S RT) ISSN: 2277-9655,www.ijesrt.com, Vol -2 Issue 10, October 2013 - SLICED RIDGELET TRANSFORM FOR IMAGE DENOISING, Ip: 4.45

3. International Journal of Engineering Research & Technology (IJERT) ISSN: 2278-0181,Vol. 2 Issue 10, October – 2013 - IMAGE DENOISING USING COMPLEX RIDGELET TRASFORM, Ip : 4

4. International Journal of Innovative Research in Computer and Communication Engineering, ISSN(Online): 2320-9801, ISSN (Print) : 2320-9798 - SLICED RIDGELET TRANSFORM FOR IMAGE DENOISING, Vol -4 Issue 6, july 2016.Impact factor 6.5
5. International Journal of Innovative Research in Computer and Communication Engineering, ISSN(Online): 2320-9801, ISSN (Print) : 2320-9798, Vol -3 Issue 4, April 2015 - SLICED RIDGELET TRANSFORM FOR IMAGE DENOISING. Impact factor 6.5.
6. International Journal of Emerging Engineering Science and Technology , Volume 1 Issue 2 -2015, www.ijeest.com - IMAGE SEGMENTATION APPROACH FOR NATURAL IMAGES USING DT CWT

7. International J ournal of Emerging Technologies in Computational and Applied Sciences (IJETCAS) www.iasir.net, , ISSN(Online): 2279-00 55 ISSN (Print) : 2279-0047, IJETCAS 15-319; © 2015, IJETCAS All Rights Reserve d P a g e 6 5 I- DESIGN OF A PRACTICAL TYPE TRANSMISSION LINES BY USING COMSOL MULTYPHYSICS 5.1
8. International journal of innovative research & development ISSN: 2278 – 0211 (Online),pg34 - 40, www.ijird.com August, 2013 Vol 2 Issue 8 - DESIGN, TESTING AND IMPLEMENTATION OF DIGITAL IMAGE PROCESSING SYSTEM FOR VIABLE SOLUTIONS.

9. International Journal Of Engineering And Computer Science, ISSN:2319-7242 Volume 2 Issue 8 August, 2013 Page No. 2468-2475 - IMPLEMENTATION OF WAVELET TRANSFORM, DPCM AND NEURAL NETWORK FOR IMAGE COMPRESSION.

10. **International Research Journal of Engineering and Technology (IRJET)**, Volume 3 Issue 6, June 2016**.** , ISSN(Online): 2395-0056 , ISSN (Print) : 2395-0072 - Automatic Fluid Level Control Using Programmable Logic Controller

11. International Journal of Engineering, Agriculture and Medicine (IJEAM) ,June 2013, Vol. 1, No. 1, pg25-29. - FIR AND IIR FILTER DESIGN FOR TRANSMISSION SYSTEMS.

12. International Journal of Science and Modern Engineering (IJISME), ISSN: 2319-6386,pg 20-23, Volume-1, Issue-9, August 2013 - ANALYSIS OF ORGANIC PHOTOVOLTAIC CELL.

13. International Journal of Integrative sciences, Innovation and Technology, eISSN 2278-1145, pg 20 - 25 Aug. 2013, Vol.2, Iss 4, - MANUFACTURE AND TECHNIQUES OF ORGANIC SOLAR CELL.

14. International Journal of Engineering, Agriculture and Medicine (IJEAM) ,June 2013, Vol. 1, No. 1, pg 30-38. - HARMONIC ELIMINATION IN SINGLE PHASE SYSTEMS BY MEANS OF A HYBRID SERIES ACTIVE FILTER USING DSP.

15. International Journal of Multidisciplinary Research Academy (I J M R A), infoijmra@gmail.com, info@ijmra.us,ISSN: 2320-0294 Volume3, Issue 11 Nov 2013 - DEVICE FOR POSITION ESTIMATION OF SURFACE MOVING VEHICLE.

16. International Research Journal of Engineering and Technology **(IRJET) : e-ISSN: 2395 -0056,** Volume: 03 Issue: 07 | July-2016, www.irjet.net **, p-ISSN: 2395-0072 -** IMPROVEMENT OF HYBRID IMAGE COMPRESSION TECHNIQUE

17. International Research Journal of Engineering and Technology **(IRJET) : e-ISSN: 2395 -0056** Volume: 03 Issue: 07 | July-2016 **,** www.irjet.net**, p-ISSN: 2395-0072: -** IMAGE DENOISING USING DIGITAL SIGNAL PROCESSOR

18. International Journal of Innovative Research in Computer and Communication Engineering, ISSN(Online): 2320-9801, ISSN (Print) : 2320-9798, Vol -4 Issue 7, April 2015 - IMAGE COMPRESSION ALGORITHMS FOR REAL TIME APPLICATIONS

Appendix-C

CURRICULUM VITAE

VANKDOTH KRISHNANAIK
H.NO: 6-2/3/8, Sainagar colony -3, Sarswathi Nagar Road No : 3, Gopalpuram,
Hanamakonda, Warangal, Telangana, India – 506 001.

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❖ **CAREER PROFILE:** I am **VANKDOTH KRISHNANAIK,** currently working as Assoc. Professor, in the **Department of Electrical & Computer Engineering**, **College of Engineering & Tech, Aksum University**, Axum, Ethiopia, North East Africa. He studied **B.E (ECE)** from **C.B.I.T, Osmania University**, Hyderabad and **M.Tech (Systems & Signal Processing)** from **J.N.U.C, J.N.T.U,** Hyderabad, A.P, India. He is having 16+ years of work experience in **Academics, Teaching, Industry & Research**. He participated and presented research papers in both national and international conferences, seminars and workshops; also published 15 research papers in national and international peer reviewed journals.

❖ **CAREER OBJECTIVE:**

I am looking forward to an opportunity where I can utilize my skills in contributing effectively to the success of the organization and also further to improve my skills by taking challenging assignments.

❖ **EDUCATION QULIFICATIONS:**

- **Master of Technology** (**Systems & Signal Processing, ECE**) from **Jawaharlal Nehru Technological University College of Engineering, JNTU,** Kukatpully, Hyderabad, Andhra Pradesh in June 2005.
- **Bachelor of Engineering** (**Electronics & communication Engineering)** from **C.B.I.T**, **Gandipet, Hyderabad, Osmania University,** Hyderabad, Andhra Pradesh in April 1999.

❖ **EXPERIENCE : 16 Years of** E**xperience.**

1. Presently working as **Associate Professor** in the Department of Electrical and computer Engineering at **College of Engineering and Tech, Aksum University Aksum, Ethiopia,** from 15th November 2012 to till date.
2. Worked as **Professor & HOD** in the Department of Electronics and communication Engineering at **Ellenki College of Engineering for women, Patel guda , BHEL, Hyderabad,** from 25th December 2010 to November 2012
3. Worked as an **Associate Professor** in the Department of M.Tech (Electronics and communication Engineering) at **VIF College of Engineering & Tech, Gandipet, X- Road, Himayath Sagar, Hyderabad** from 25th September 2009 to 24th December 2010.
4. Worked as an **Associate Professor** in the Department of Electronics and communication Engineering at **Hi-point college of Engineering. & Tech, Chilkur, Moinabad, Hyderabad** from 18th July 2003 to 24th September 2009.
5. Worked as a **Hardware Engineer** in "**PACIFIC ELETRONIC PVT LED SEC-BAD"** from 6th June 1999 to 10th Jan 2002.

❖ TECHNICAL INTERNATIONAL PAPER PRESENTATIONS (JOURNALS):

S.No	TITLE OF PAPER	JOURNAL	DATE
1.	SLICED RIDGELET TRANSFORM FOR IMAGE DENOISING	I J E S RT	Vol -2 Issue 10, October 2013
2.	IMAGE DENOISING USING COMPLEX RIDGELET TRASFORM	I J E R T	Vol - 2 Issue 10, October 2013
3.	SLICED RIDGELET TRANSFORM FOR IMAGE DENOISING	I OSR-JCE	Vol -14 Issue 1, Sep. - Oct. 2013
4.	DESIGN, TESTING AND IMPLEMENTATION OF DIGITAL IMAGE PROCESSING SYSTEM FOR VIABLE SOLUTIONS	I J I R D	Vol - 2 Issue 8, August 2013
5.	IMPLEMENTATION OF WAVELET TRANSFORM DPCM & NEURAL NETWORK FOR IMAGE COMPRESSION	I J E C S	Vol -2 Issue 8, August 2013 pg No. 2468-2475
6.	DEVICE FOR POSITION ESTIMATION OF SURFACE MOVING VEHICLE	I J M R A	Vol - 3 Issue 11, November 2013
7.	FIR AND IIR FILTER DESIGN FOR TRANSMISSION SYSTEMS.	I J E A M	Vol -1 Issue 1, June 2013 No. 1, Pg 25-29
8	HARMONIC ELIMINATION IN SINGLE PHASE SYSTEMS BY MEANS OF A HYBRID SERIES ACTIVE FILTER USING DSP.	I J E A M	Vol -1 Issue 1, June 2013 Pg 30-38
9	ANALYSIS OF ORGANIC PHOTOVOLTAIC CELL	I J I S M E	Vol-1 Issue-9, August 2013
10	MANUFACTURE AND TECHNIQUES OF ORGANIC SOLOR CELL	I J I I T	Vol -2 Issue 4, August 2013 Pg 20-25

❖ PROFESSIONAL WORK EXPERIENCE :

- ✓ **I worked as an AICET work In-charge at VIF college, Ellenki College**
- ✓ **I worked as Examination Branch in charge at Hi-Point college.**
- ✓ **I Guided 35 B.Tech Projects and 5 M.Tech Projects.**
- ✓ **I Participated many workshops in different colleges.**
- ✓ **I Establish all kinds of Electronics & comm. labs for Engineering UG, PG.**

- **TECHNICAL SKILLS:**
  - **Programming Languages** : C,C++,JAVA,SQL,MATLAB ,CCS
  - **Operating Systems** : Windows XP/2000/NT/98,MS-DOS,Unix

- **PROFESSIONAL OBJECTIVES:**
  - To work in the institution with utmost dedication and commitment.
  - To assist all senior Officials and colleagues.

- **WORKSHOPS AND SEMINARS**

S. No	DETAILS	Conducted by	DATE
1.	**SPEAKER DEPENDENT ISOLATED HINDI WORD RECOGNITION SYSTEMS**	Jyothishmathi College of Engineering & Tech,	2/2/2007 to 3/2/2007
2.	**A PERFORMANCE STUDY OF PARALLEL FFT IN CLOS AND MESS NETWORKS**	Vidhya Bharati Institute of Tech, Warangal	14/2/2007 to 15/2/2007
3.	**3Days workshop on Embedded System Applications**	Hi-Point college of Engg, Hyderabad	10.11.2008 to 12.11.2008
4.	**Workshop On Controller Area Network**	ISM, Bangalore	18/07/2009
5	**5 Days Workshop on Advance Digital Signal Processing**	Pujya shri madhavanji I. S & Tech, Hyderabad	26.12.2010 to 31.12.2010
6	**Organized Mini projects 2 Days workshop**	Ellenki College of Engineering & Tech, Hyd.	21 .11.2011 to 22.11.2011
7	**VCET – INGNIUM – 2K11 Expert Lecture on ADSP**	VIF College of Engineering & Tech, Hyd	28.07.2012 to 29.07.2012

- **BOOK PUBLICATIONS : 5**
  1. **Microcomputer and Interface : ISBN 978-3-659-68484-5**
  2. **Logic Design and Applications : ISBN 978-3-659-39723-3**
  3. **Introduction to Machines : ISBN 978-3-659-51431-9**
  4. **Digital Signal Processing : ISBN 978-3-659-68749-5**
  5. **Research Methods & Presentation : ISBN 978-3-659-87517-5**

❖ **PROFESSIONAL MEMBERSHIP :**

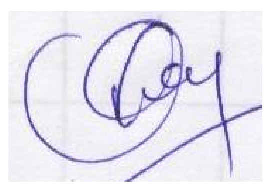
- **Lifetime Membership on ISRD (International Society For Research And Development)**

  Membership ID : M3140900627 As A MEMBER

❖ **PERSONAL PROFILE :**

Name	: Vankdoth Krishnanaik
Fathers Name	: V.Dasharatha Naik
Date of Birth	: 10th Jan 1976
Permanent Address	: Post: Challagariga, Chityal, Warangal – 506356.
Passport No.	**: K6880448**, Hyderabad, Andhra Pradesh, India

I hereby declare that the above-mentioned information is true, complete & correct to the best of my knowledge and belief.



Place: Warangal

Thanks and Regards

(V.Krishnanaik)