Sudan University of Science and Technology
College of Postgraduate Studies

Image De-noising and Compression Using Discrete Wavelet Transform

تقليل الضجيج و ضغط الصور بإستخدام تحويل المويجات المتقطعة

A thesis Submitted in Partial Fulfillment of the Requirement for the Degree of M.Sc. in Electronics Engineering (Communications Engineering)

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الأية

قال تعالي:

[شهد الله أنه لا إله إلا هو و الملائكة و أولوا العلم قائما بالقسط لا إله إلا هو العزيز الحميد]

[آل عمران(١٨)] صدق الله العظيم.

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Abstract

Image denoising and compression has remained a fundamental problem in the field of image processing aiming at the removal of noise which may corrupt an image during its acquisition or transmission while sustaining its quality. Wavelets gave a superior performance in image denoising and compression due to its properties such as multi resolution.In this thesis an adaptive method of image denoising in the wavelet sub band domain has been proposed.The idea behind using this technique the DWT process the horizontal ,vertical and diagonal details of the image without affect the approximation details, it improves the performance of the mathematical software(MATLAB) of denoising function. The experimental evaluation shows that it removes noise significantly and more effectively than the existed denoise technique it show that by applying different wavelet family types, different noise level and different level of decomposition.In the second phase of thesis after image became free of noise the compression technique jpeg 2000 has been applied to the image due to the development and demand of multimedia product grows increasingly fast, contributing to insufficient bandwidth of network and storage of memory device. Therefore, the theory of data Compression is useful because it helps reduce the consumption of expensive resources such as hard disk space or transmission bandwidth.In this thesis, the fundamental theory of image compression in chapter 2 has been briefly introduced,two typical standards JPEG and JPEG 2000 will be described and implemented to the denoise image in chapter 4. The last given image is compressed denoise image without degraded its quality.

المستخلص

يعد تقليل الضجيج وضغط الصور من المشاكل الأساسية في مجال معالجة الصور ،ويطرأ الضجيج على الصور في مراحل إلتقاطها ونقلها .تعطي تقنية المويجات المتقطعة أداءا فائقا في إزالة الضجيج من الصورة وذلك لما تمتع به من خواص كالدقة المتعددة و الوضوح المتعدد . نقدم في هذه الأطروحة طريقة فعالة لإزالة الضجيج من الصور دون أن يؤثر ذلك على جودة الصورة ومن ثم نقوم بضغط الصورة ليتم نقلها أو تخزينها بصورة مثلى . وتقترح التقنية المستخدمة في هذه الأطروحة تقدير المستوى الحرج المقبول لنقاء الصورة والفكرة من وراء إستخدام هذه التقنية عملية تحسين التفاصيل الأفقية والرأسية والقطرية للصورة دون أن تؤثر على التفاصيل التقريبية وبذلك فإن أداء البرنامج الرياضي (الماتلاب) يتحسن ، فعالية هذه الطريقة بإستخدام تعتمد على بتقييم مستويات الحد الأدنى لنقاء الصور بتجربة عدة مستويات للتحويل المويجي و عدة مستويات للضجيج وعدة مستويات لتقليل الضجيج وتنقية الصورة وفق معايير خاصة و قد أوضحت التجارب فعالية هذه التقنية في تقليل الضجيج بصورة فعالة و مثالية مقارنة بالتقنيات الأخرى .في الجزء الثاني من هذه الأطروحة وبعد تقليل الضجيج في الصورة فإنه يتم تطبيق تقنية الجبيج ٢٠٠٠ لضغط الصورة وذلك لانه وفي السنوات الأخيرة ونسبة للتطورالسريع والطلب المتزايد على منتجات الوسائط المتعددة أصبح عرض النطاق الترددي غير كافي ونسبة للتخزين المكلف في وحدات التخزين . ولذلك فإن نظرية ضغط البيانات تعتبر من الأهمية بمكان للحد من تكرار البيانات لتوفير المساحة في الذواكر و إستخدام النطاق الترددي بصورة مثلى. في هذا البحث نقدم بإيجاز النظريةالأساسية في ضغط الصورة في الفصل الثاني و نقوم بتفصيل وتطبيق الضغط بطريقة ال (جيبج٢٠٠٠) في الفصل الرابع من هذا البحث وتظهر النتائج الحصول على صورة مضغوطة خالية من الضجيج مع جودة عالية في مضمونها .

Table of Contents

List of Figures

List of Tables

List of Abbreviations

1D	one dimensional
2D	two dimensional
3D	three dimensional
AWGN	Additive White Gaussian Noise
BDCT	Block-Based Discrete Cosine Transform
BMP	Bitmap Image
CWT	Continuous wavelet transform
DCT	Discrete cosine transform
DFT	Discrete Fourier transform
DNA	DeoxyriboNucleic Acid
DWT	Discrete wavelet transform
ECG	electrocardiogram
FFT	Fast Fourier Transform
GCV	generalized cross validation
GGD	generalized Gaussian distribution
GIF	Graphics Interchange Format
GMM	Gaussian mixture model
HMM	Hidden Markov Models
HVS	Human Visual System
ICA	Independent Component Analysis
JPEG	Joint Photographic Experts Group
MAP	Maximum A Posteriori
MIT	Massachusetts Institute of Technology
MPEG	Moving Picture Experts Group

MRA	Multi resolution analysis
MRI	Magnetic resonance imaging
MSE	Mean Square Error
PDF	Probability density function
PNG	Portable Network Graphics
PSNR	Peak signal-to-noise ratio
RGB	Red Green Blue
RF	Radio Frequency
SIWPD	Shift Invariant Wavelet Packet Decomposition
SNR	Signal-to-noise ratio
STSA	Short time spectral amplitude
SURE	Stein's unbiased risk estimate
TIFF	Tagged Image File Format
UDWT	Undecimated Wavelet Transform
UUP	Uniform Uncertainty Principle
WT	Wavelet Transform

List of Symbols

z	a random variable
μ	mean value (statistical average)
σ	standard deviation
σ^2	statistical variance
$p_G(\cdot)$	PDF of the Gaussian distribution
M	row number (of a given matrix)
K	signal sparsity
N	number of sample
D	input data
$C(D)$	generates data
$D+$	reconstructs the data

1 Chapter One: Introduction

1.1 Preface

1.1.1 Image De-noising

The image is said to be more expressive than thousand words. The noise can get introduced in the image in stages of image acquisition, compression and transmission. There are many other causes too, like hardware faults in the camera lens, lesser processing power etc. This noise introduced in image produces undesired elements in image which are not soothing to the human eye so it is a priority to reduce the noise in image to as low as possible. The domain which deals with the noise elimination is known as image de-noising. The traditional way of image de-noising is filtering. Recently, a lot of research about non-linear methods of signal de-noising has been developed [1].

These methods are mainly based on thresholding the Discrete Wavelet Transform (DWT) coefficients, which have been affected by a noise. Although Fourier transform is a powerful tool for analyzing the components of a stationary signal. But it is failed for analyzing the non stationary signal where as wavelet transform allows the components of a non-stationary signal to be analyzed. Wavelet based de noising in 2D images has been a popular research work in the past few years because the wavelet can analyze the signal at different frequencies with different resolutions. This is known as multi resolution analysis (MRA). Medical images often corrupted by noises due to some factors such as machine specifications, detector specifications.

Despite Wavelet basis is have irregular shape, they are able to perfectly reconstruct functions with linear and higher order polynomial shapes, Wavelets allow complex information such as music, speech, images and patterns to be decomposed into elementary forms at different positions and scales and subsequently reconstructed with high precision [2].

1.1.2 Image Compression

Data compression is concerned with being able to represent a given mass of data more concisely easier for storage and transmission .while retaining the essential information of the original. There are two basic kinds of compression schemes: lossless and lossy. In the case of lossless compression one is interested in reconstructing the data exactly, without any loss of information. Lossy compression techniques involve some loss of information, and data that have been compressed using lossy techniques generally cannot be recovered or reconstructed exactly. In return for accepting this distortion in the reconstruction, we can generally obtain much higher compression ratios than is possible with lossless compression. In many applications, this lack of exact reconstruction is not a problem. For example, when viewing a reconstruction of a video sequence, the fact that the reconstruction is different from the original is generally not important as long as the di7erences do not result in annoying artifacts. Thus ,video is generally compressed using lossy compression. With lossless compression the reproduction is identical to the original, and hence, quality is not an issue. In the case of lossy compression, however, the reproduction is only an approximation to the original image. Measurement of quality is thus an issue with lossy compression. In the context of lossy compression, we usually are ready to accept an error, as long as the quality after compression is acceptable. One of the methods to achieve this goal is to employ the wavelet transform. A wavelet transform is well localized in both space and frequency domains and is very similar to the mechanisms of human vision system. Thus the wavelet transform matches well with human visual system characteristics. From an image coding point of view, this tends to contribute to good image quality [3].

1.1.3 Properties of Wavelet Transform

A wavelet transform can be used to decompose or divide a signal into small wavelets and in wavelet theory , it is possible to obtain a good estimation of the given function by using only a few coefficients which is a great attainment as compared to Fourier transform.

One of the main advantages of wavelets is that they provide a concurrent fixing or localization in domain of time and frequency. Wavelets also use fast wavelet transform, so it is very fast.

Wavelet transform can frequently squeeze or de-noise a signal in absence of considerable degradation.
Wavelets have the advantage of being able to divide the pure details in a signal. Smaller wavelets can be applied to dissociate the most elementary details in a signal, while very large wavelets can identify other details of coarse analysis.
Wavelet theory is competent to declare aspects of data that other signal analysis method misses. The features like breakdown points and segregation in higher order derivatives are perfect example for this [4].

1.1.4 Application of Wavelet Transform

Wavelets has many applications. For example, it is used to extract features from ECG data. Other applications include data and image compression, extraction of spatio-temporal features from 3D+time MRI data and image de-noising.

1.2 Problem Statement

This study targets the problem of compression and de-noising of images. An image is often corrupted by noise in its acquisition and transmission. For example, medical images normally have a problem of high level components of noises. Another major issue is that using a Fourier basis fails to reconstruct functions with linear and higher order polynomial shapes. On the other hand, in terms of compression, the time required for images to be sent over the Internet or downloaded from web pages is crucial, and also the storage of data in a given amount of disk or memory space.

1.3 Proposed Solution

The central idea to wavelets is to analyze (a signal) according to scale .Imagine a function that oscillates like a wave in a limited portion of time or space and vanishes outside of it. It can be used to decompose or divide a signal into small wavelets and in wavelet theory, it is possible to obtain a good estimation of the given function by using only a few coefficients which is a great attainment as compared to Fourier transform. Many images you see on the Internet today have undergone compression for various reasons. Image compression can benefit users by having pictures load faster and web pages use up less space on a Web host. Image compression does not reduce the physical size of an image but instead compresses the data that makes up the image into a smaller size [5].

1.4 Objectives

The objectives of this study are representing signals with a high degree of scarcity. Presentation of an effective and low complexity image de-noising algorithm using DWTs, which will recover an image from noise contamination effectively. In other words provision of smoothness and better edge preservation image, a good estimation of the given function could be obtained by using only a few coefficients to increase the peak signal to noise ratio (PSNR) and in the same time decreasing mean sugared error (MSE). The second part of the project after de-noising the image is compress it which facilitates the efficient transmission and storage of digital data,and develops the optimal algorithm for image compression.

1.5 Methodology

The proposed de-noising algorithm is will be performed in MATLAB simulation environment and the results will be compared accordingly [5]. the algorithm summed up to the following steps.

1. A four level DWT transforms the noise-corrupted image.
2. Estimate The standard deviation of noise will be estimated with one of the proposed methods.
3. For each sub band (except the low pass or approximation sub band), apply hard or soft threshold to the sub band coefficients.
4. Reconstruct the image by employing the inverse DWT.

Secondly The JPEG 2000 compression engine (encoder and decoder) is illustrated in block diagram form in figure (1.2)at the encoder, the

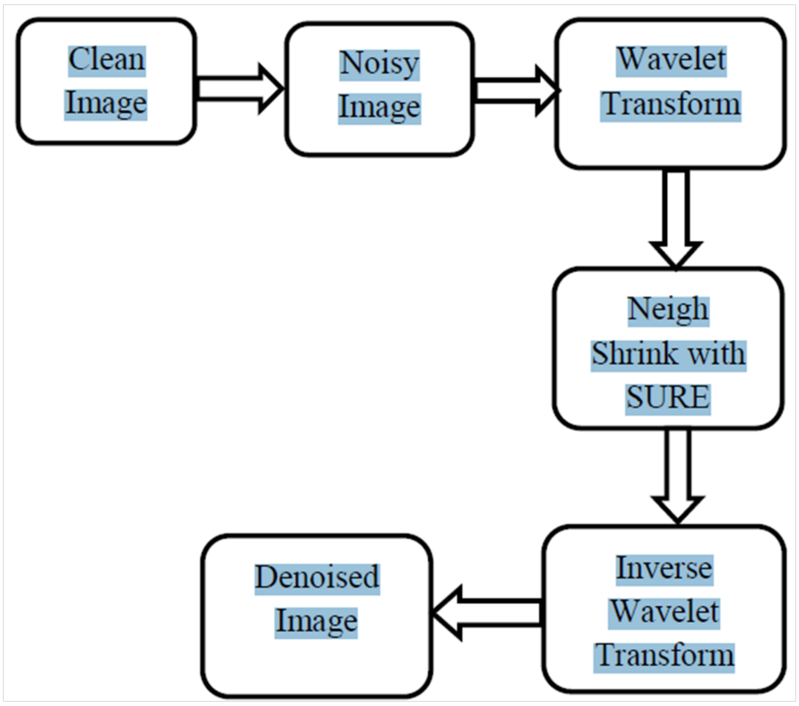

Figure 1.1: Proposed Algorithm for wavelet de noising with neigh shrink

discrete transform is first applied on the source image data. The transform coefficients are then quantized and entropy coded before forming the output code stream (bit stream). The decoder is the reverse of the encoder. The code stream is first entropy decoded, de-quantized , and inverse discrete transformed, thus resulting in the reconstructed image data. [6]

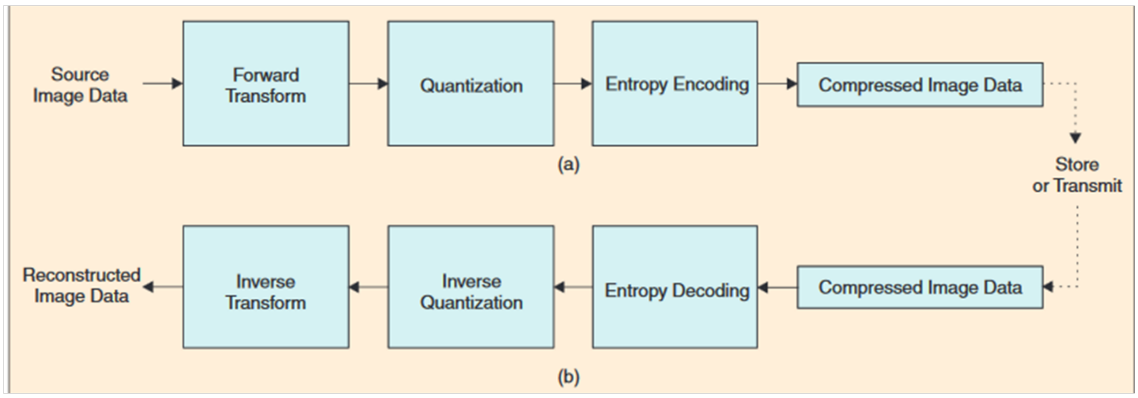

Figure 1.2: General block diagram of the JPEG 2000 (a) encoder and (b) decoder

1.6 Thesis organization

The thesis is organized as follows. Chapter 2 discusses a literature review of image processing techniques. Chapter 3 discusses the wavelet transform. In the second part of this chapter, we systematically describe different wavelet de-noising approaches. In addition, we Discuss image compression techniques and link them to the employed method in this study. Also, this chapter, considers the compression technique JPEG 2000. Chapter 4 presents the implementation, simulation results and experimental restoration results. This includes a comparison with other de-noising methods. Finally, chapter 5 presents conclusions and recommendation.

2 Chapter Two: Literature Review

2.1 Background

Digital Images are electronic snapshots taken of a scene or scanned from documents, such as photographs, manuscripts, printed texts, and artwork. The digital image is sampled and mapped as a grid of dots or picture elements (pixels). Digital images play an important role in research and technology such as geographical information system as well as it is the most vital part in the field of medical science [7]. Therefore, these images are required in accurate form so that they can be used effectively. But during their transmission and reception they are usually affected by noise. The original meaning of ”noise” was and remains ”unwanted signal”. Image noise is random (not present in the object imaged) variation of brightness or color information in images, and is usually an aspect of electronic noise. Noise removal algorithm is the process of removing or reducing the noise from the image [7]. This chapter attempts to give a brief description about the sources of noise and the various noise models.

The existing traditional image de-noising methods can be broadly divided into two categories: one is in spatial domain, the main use of various smoothing template and image de-convolution processing, in order to achieve the purpose of noise suppression or elimination; Another is the transform domain method, we transform the image, and then choose the appropriate frequency band pass filter, the inverse transformation to obtain the image de-noising. Spatial domain de-noising method often uses the mean filter, median filtering, Wiener filtering and image average method. The median filtering method is a method of nonlinear signal processing, its basic thought is in digital image, a point value by the median neighborhood of the point in the template instead of several point. Is simply to use a window, the mobile at various points along the image pixel values, window center points of using the median of all pixels in the window for replacement. The shape and size of the window will have obvious influence on the filtering effect. Because standard median filter is a kind of non parameter estimation, so there will be a certain blindness. As a kind of adaptive de-noising method, Wiener filter according to the local variance of the image value, output to adjust the filter, to restore the image of the original image is the ultimate goal of the minimum mean square error. But because of the interference signal, input process depends on the external environment, and these statistics are unknown and changing factors. Aiming at the defects of the algorithm, the researchers still need further research and exploration [8].

The basic idea of transform domain is: first, some noise on the image transformation, transformation to transform domain; then, according to the transform coefficients in the transform domain processing; finally, the inverse transform of the image to the original space, achieve the purpose of removing noise. The low-pass filter is: in the spatial domain, two-dimensional convolution by using a low pass convolution template, so as to achieve the purpose of image de-noising. Methods of image space common conversion transform domain are: Fourier transform, Walsh Hadamard transform, discrete cosine transform, wavelet transform and the recent development of multi scale geometric analysis method. Because many signal can not be effectively analysis in spatial domain, and after the transformation coefficients distribution becomes obvious, in the frequency domain signals can be effectively analyzed. This can be used to all kinds of image processing tasks, and also makes this method becomes a hot image de-noising research [9].

2.2 Related Work

In recent years, wavelet analysis technique was also applied to the field of image processing, and the application effect is good. At present, the wavelet method is widely used in image de-noising, main methods: wavelet transform modulus maximum de-noising, wavelet coefficient correlation de-noising and threshold shrinkage de-noising. The basic principle of wavelet de-noising is: the first step is to decompose the noisy image using wavelet; the second step to extract the wavelet coefficients of image wavelet coefficients and noise removal; third step transform reconstruction image noise removal. More used in the de-noising process [10].

Although wavelet de-noising method has become a main research direction of image de-noising, but it is also inadequate, with one kind of noise is very similar to that of image, then wavelet analysis method is very difficult to distinguish between the image information and noise information, of course this case removal effect is not very satisfactory. Therefore, to further expand the research field of de-noising method. At the same time, by using the method of partial differential equation for image processing, is a newly emerging area developed in the recent years. Stronger local adaptability and flexibility makes PDE method has become an effective image processing technology. This method in image de-noising can protect the edge of the image better. Through research, we can found that the following two questions are the key and difficult problems in the field of signal processing: one is due to the Nyquist sampling high sampling frequency, resulting in a large number of sample data; two is the sampling and compression mode, make a large number of data's utilization rate is not high, resulting in the waste of sensing element, time and memory space. To some extent these problems restrict the development of signal and information processing. Aiming at these problems, in recent years, the birth of a new theory of compressed sensing. The methods used to obtain the signals at the same time, the data below the Nyquist frequency sampling, compression, need to use reconstruction algorithm appropriate restore enough data points.

The utility model has the advantages of reducing sampling data, the storage space is saved enough amount of information under the premise, and combined the traditional data acquisition and compression, but there is no complex data encoding, it is very suitable for the small equipment occasions, so the compressed sensing in the field of signal processing has become a new research direction [3].

Compressed sensing theory as the signal processing in the field of a new research direction, since 2006 the formal papers, soon it is paid more attention by the research in related fields at home and abroad. At present, the area is mainly focused on the research work of theory, research foundation for: Terence Tao, Emmanuel Candès, David Donoho [11] who have the theory framework of compressed sensing, a sensing matrix is given to satisfy the sufficient condition, which is consistent with the Uniform Uncertainty Principle(UUP); between the sensor matrix's row number M and the signal sparsity K must meet$M \geq K \log(N)$, [12] and published a series of important papers [13]. In addition, there are many specific problems about solving the sensing matrix and reconstruction algorithm of two major aspects of the research results. Study on the sensing matrix, matrix of the current selection is random, such as Gauss matrix or Bernoulli matrix. How to construct the sensing matrix is an open problem in this field at present. DeVore using polynomial method to obtain satisfy UUP feature matrix, but it only for sparse K smaller case, the problem is far from solved. When it comes to reconstruction of the signal, [14] There are many documents will match tracking and optimization method is introduced to solve the problem, but the discussion on the algorithm convergence and stability problems. Considering hardware implementation, Professor Baraniuk, from Rice university, developed single pixel camera, which attracted the attention of the domestic and international numerous media. Furthermore, Professor Wald [8], from MIT, developed an MRI RF pulse instrument. Professor Freeman [6], from MIT as well, developed a coded aperture camera and finally Milenkovic [15] Illinois State University, developed DNA microarray sensors. However, in addition to the single pixel camera, Rice University (the expensive hardware cost, low efficient reconstruction algorithm), other hardware are lack of strict and effective theory of compressed sensing matrix discriminant analysis. After nearly two years of development, the compressed sensing has achieved many important results in the theory, many researchers have begun to put into practical applications, such as information, medical science etc [16].

2.3 Noise Sources

During image transmission and image acquisition noise is introduced in the image. There may be different reasons for the introduction of noise in the image. The number of pixels corrupted in the image determines the quantification of the noise [17]. The important sources of noise in the digital images are the environmental conditions, which may affect the imaging sensor, low light and sensor temperature may which introduces noise in the image, dust particles present in the scanner which may introduce noise in the digital image and finally the interference in transmission channel [17]

2.3.1 Types of Noise Models

Digital images are prone to a variety of types of noise. Noise is the result of errors in the image acquisition process that result in pixel values that do not reflect the true intensities of the real scene. Depending upon the type of disturbance the noise can affect the image to a different extent. Different noise models include the Gaussian noise model, [18]

2.3.1.1 Gaussian Noise Model

It is also called as electronic noise because it arises in amplifiers or detectors. Gaussian noise caused by natural sources such as thermal vibration of atoms and discrete nature of radiation of warm objects. Gaussian noise generally disturbs the gray values in digital images. That is why Gaussian noise model essentially designed and characteristics by its PDF or normalizes histogram with respect to gray value. This is given as [17]

$$p_G(z) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(z-\mu)^2}{2\sigma^2}} \tag{2.1}$$

where σ^2 is the variance and μ is the mean value.

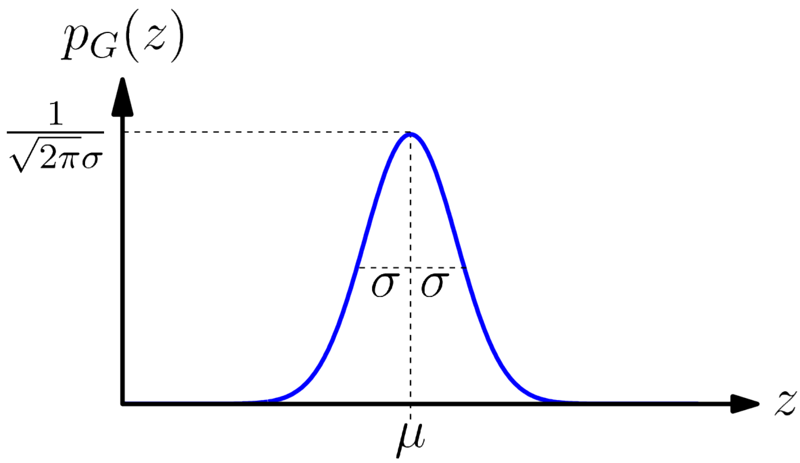

Figure 2.1:

2.3.1.2 Salt and Pepper Noise Model

This is also called data drop noise because statistically its drop the original data values. This noise is also referred as salt and pepper noise. However the image is not fully corrupted by salt and pepper noise instead of some pixel values are changed in the image. Although in noisy image, there is a possibilities of some neighbors does not change [17].

$$p(z) = \begin{cases} p_a & \text{for } z = a \\ p_b & \text{for } z = b \\ 0 & \text{otherwise} \end{cases} \tag{2.2}$$

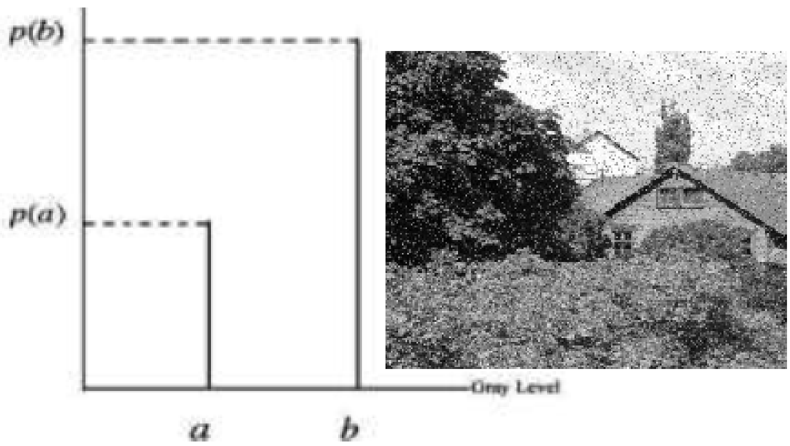

Figure 2.2: PDF of Salt and Pepper Noise

2.3.1.3 Periodic Noise

This noise is generated from electronics interferences, especially in power signal during image acquisition. This noise has special characteristics like spatially dependent and sinusoidal in nature at multiples of specific frequency. Its appears inform of conjugate spots in frequency domain. It can be conveniently removed by using a narrow band reject filter or notch filter [17].

2.3.1.4 Photon Noise (Poisson Noise)

The appearance of this noise is seen due to the statistical nature of electromagnetic waves such as X-rays, visible lights and gamma rays. The X-ray and gamma ray sources emitted number of photons per unit time. These rays are injected in patients body from its source, in medical X-rays and gamma rays imaging systems. These sources are having random fluctuation of pho-

Figure 2.3: Periodic Noise

tons [17]. This noise is also called as quantum (photon) noise or shot noise.

Figure 2.4: Poisson Noise

2.3.1.5 Exponential Noise

The pdf of exponential noise is given as

$$p(z) = \begin{cases} ae^{-az} & z \geq 0 \\ 0 & z < 0 \end{cases} \tag{2.3}$$

2.3.1.6 Uniform Noise

The noise caused by quantizing the pixels of a sensed image to a number of discrete levels is known a quantization noise. It has an approximately uniform distribution. Though it can be signal dependent, it will be signal

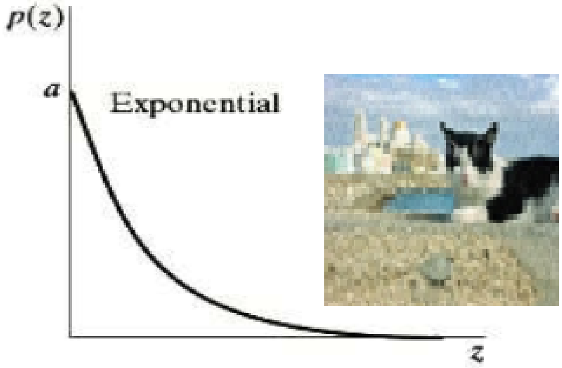

Figure 2.5: PDF of Exponential Noise

independent if other noise sources are big enough to cause dithering, or if dithering is explicitly applied.

$$p(z) = \begin{cases} \dfrac{1}{b-a} & a \leq z \leq b \\ 0 & \text{otherwise} \end{cases} \tag{2.4}$$

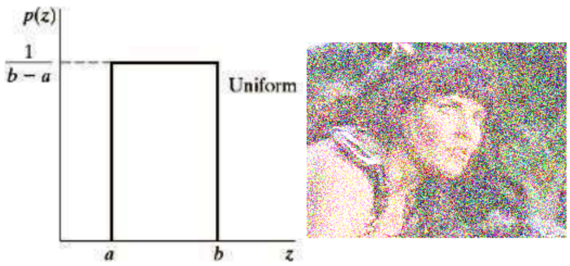

Figure 2.6: PDF of Uniform Noise

2.3.1.7 Gamma Noise

Gamma noise is generally seen in the laser based images. It obeys the Gamma distribution [19]

$$p(z) = \begin{cases} \dfrac{a^b z^{b-1}}{b-1!} e^{-az} & z \geq 0 \\ 0 & \text{otherwise} \end{cases} \tag{2.5}$$

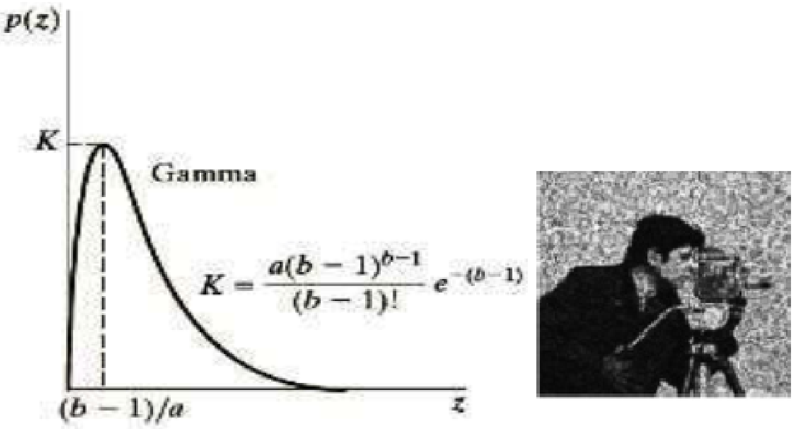

Figure 2.7: PDF of Gamma Noise

2.3.1.8 Rayleigh Noise

Rayleigh noise presents in radar range images.

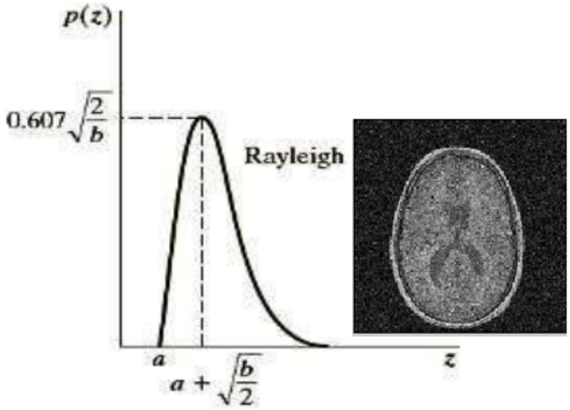

Figure 2.8: PDF of Rayleigh Noise

2.3.1.9 Brownian Noise (Fractal Noise)

Colored noise has many names such as Brownian noise or pink noise or flicker noise or $1/f$ noise. In Brownian noise, power spectral density is proportional to square of frequency over an octave i.e., its power falls on ¼ th part (6 dB per octave). Brownian noise caused by Brownian motion. Brownian motion seen due to the random movement of suspended particles in fluid. However this noise follows non stationary stochastic process. This process follows normal distribution. Statistically fractional Brownian noise is referred to as fractal noise. Fractal noise is caused by natural process [17].

2.3.1.10 Structured Noise

Structured noise are periodic, stationary or non stationary and a periodic in nature. If this noise is stationary, it has fixed amplitude, frequency and phase. Structured noise are caused by interferences among electronic components. Noise presents in communication channel are in two parts, unstructured noise (u) and structured noise (s). structured noise is also called low rank noise. In a signal processing, it is more advantagable (more realistic) to considering noise model in a lower dimensionality space [17]. Therefore, noise is added to the image during image acquisition and to a lesser or greater extent affects the image. So, the noise models are an important part of digital image processing. Without having the knowledge about these models it is nearly impossible to remove the noise from the image and perform de-noising actions.

2.3.2 Evolution of Image De-noising Research

Removing noise from the original signal is still a challenging problem for researchers. There have been several published algorithms and each approach has its assumptions, advantages, and limitations. This paper presents a review of some significant work in the area of image de-noising. After a brief introduction, some popular approaches are classified into different groups and an overview of various algorithms and analysis is provided. Insights and potential future trends in the area of de-noising are also discussed [20]

Digital images play an important role both in daily life applications such as satellite television, magnetic resonance imaging, computer tomography as well as in areas of research and technology such as geographical information systems and astronomy. Data sets collected by image sensors are generally contaminated by noise. Imperfect instruments, problems with the data acquisition process, and interfering natural phenomena can all degrade the data of interest. Furthermore, noise can be introduced by transmission errors and compression. Thus, de-noising is often a necessary and the first step to be taken before the images data is analyzed. It is necessary to apply an efficient de-noising technique to compensate for such data corruption.

Image de-noising still remains a challenge for researchers because noise removal introduces artifacts and causes blurring of the images. This chapter describes different methodologies for noise reduction (or de-noising) giving an insight as to which algorithm should be used to find the most reliable estimate of the original image data given its degraded version. Noise modeling in images is greatly affected by capturing instruments, data transmission media, image quantization and discrete sources of radiation. Different algorithms are used depending on the noise model. Most of the natural images are assumed to have additive random noise which is modeled as a Gaussian. Speckle noise [20] is observed in ultrasound images whereas Rician noise [1] affects MRI images. The scope of the paper is to focus on noise removal techniques for natural images. [20]

Image De-noising has remained a fundamental problem in the field of image processing. Wavelets give a superior performance in image de-noising due to properties such as sparsity and multi resolution structure. With Wavelet Transform gaining popularity in the last two decades various algorithms for de-noising in wavelet domain were introduced. The focus was shifted from the Spatial and Fourier domain to the Wavelet transform domain. Ever since Donoho's Wavelet based thresholding approach was published in 1995, there was a surge in the de-noising papers being published. Although Donoho's concept was not revolutionary, his methods did not require tracking or correlation of the wavelet maxima and minima across the different scales as proposed by Mallat [13]. Thus, there was a renewed interest in wavelet based de-noising techniques since Donoho [21] demonstrated a simple approach to a difficult problem.

Researchers published different ways to compute the parameters for the thresholding of wavelet coefficients. Data adaptive thresholds were introduced to achieve optimum value of threshold. Later efforts found that substantial improvements in perceptual quality could be obtained by translation invariant methods based on thresholding of an Un decimated Wavelet Transform . These thresholding techniques were applied to the non orthogonal wavelet coefficients to reduce artifacts. Multi wavelets were also used to achieve similar results. Probabilistic models using the statistical properties of the wavelet coefficient seemed to outperform the thresholding techniques and gained ground. Recently, much effort has been devoted to Bayesian de-noising in Wavelet domain. Hidden Markov Models and Gaussian Scale Mixtures have also become popular and more research continues to be published. Tree Structures ordering the wavelet coefficients based on their magnitude, scale and spatial location have been researched. Data adaptive transforms such as Independent Component Analysis (ICA) have been explored for sparse shrinkage.

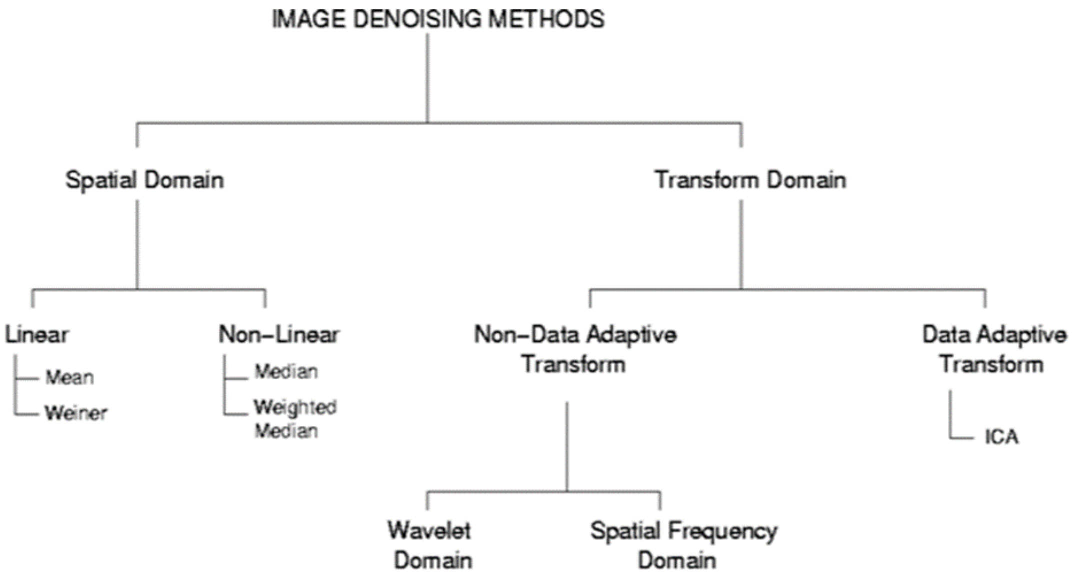

Figure 2.9: Classification of De-Noising Algorithm

The trend continues to focus on using different statistical models to model the statistical properties of the wavelet coefficients and its neighbors. Future trend will be towards finding more accurate probabilistic models for the distribution of non-orthogonal wavelet coefficients [11].

2.3.3 Classification of Image De-noising Algorithms

As shown in Figure 2.9, there are two basic approaches to image de-noising, spatial filtering methods and transform domain filtering methods.

2.3.4 Spatial Filtering

A traditional way to remove noise from image data is to employ spatial filters. Spatial filters can be further classified into non-linear and linear filters [22].

2.3.4.1 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, rank conditioned rank selection, and relaxed median [16] have been developed to overcome this drawback [22].

2.3.4.2 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 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 Johnstone proposed the wavelet based de-noising scheme in [23].

2.3.5 Transform Domain Filtering

The transform domain filtering methods can be subdivided according to the choice of the basis functions. The basis functions can be further classified as data adaptive and non-adaptive. Non-adaptive transforms are discussed first since they are more popular.

2.3.5.1 Non-Adaptive thresholds

VisuShrink [23], 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.

2.3.5.2 Adaptive Thresholds

SureShrink [23], uses a hybrid of the universal threshold and the SURE [Stein's Unbiased Risk Estimator] threshold and performs better than VisuShrink. BayesShrink [23] 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 [24] replaces wavelet coefficient with the weighted average of neighborhood coefficients to minimize generalized cross validation (GCV) function 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 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.

2.3.5.3 Spatial-Frequency Filtering

Spatial-frequency filtering refers use of low pass filters using Fast Fourier Transform (FFT). In frequency smoothing methods [10] 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. Operations in the wavelet domain can be subdivided into linear and nonlinear methods.

2.3.5.4 Data-Adaptive Transforms

Recently a the method called Independent Component Analysis (ICA) has gained wide spread attention. The ICA method was successfully implemented in [24] in de-noising Non-Gaussian data. One exceptional merit of using ICA is it's assumption of signal to be Non-Gaussian which helps to de-noise images with Non-Gaussian as well as Gaussian distribution. Drawbacks of ICA based methods as compared to wavelet based methods are the computational cost because it uses a sliding window and it requires sample of noise free data or at least two image frames of the same scene. In some applications, it might be difficult to obtain the noise free training data.

2.4 Image compression

Image compression, the art and science of reducing the amount of data required to represent an image is one of the most useful and commercially successful technologies in the field of digital image processing. The number of images that are compressed and decompressed daily is staggering and the compression and decompressions themselves are virtually invisible to the user [25]. Digital images are widely used in a number of various applications. It is seen that uncompressed digital images would need large storage capacity and wider transmission bandwidth for effective utilization of picture detail in modern applications. Therefore, the effective image compression solutions are becoming more critical with the recent growth of data intensive, multimedia based web applications [4]. In the development of efficient compression techniques will continue to design challenge for future communication system and advanced multimedia applications. During image compression quality of decompressed image is also criterion for evaluation of given coding scheme. In the process of compression decompression various artifacts such as blocking artifacts, blur artifacts, rising or edge artifacts are observed . Blocking artifacts often exist in the images compressed by standards such as JPEG and MPEG which causes serious image degradation [26]. Blocking artifacts is a prevailing degradation caused by Block-Based Discrete Cosine Transform (BDCT) coding technique under low bit rate conditions [27].

There are two fundamental components of compression are *redundancy* and *irrelevancy reduction*. Redundancy reduction aims at removing duplication from the signal source. Irrelevancy reduction omits parts of the signal that will not be noticed by the signal receiver, namely the Human Visual System (HVS). In general, three types of redundancy can be identified. First, *coding Redundancy*, in which fewer bits to represent frequently occurring symbols. Second, *Inter-pixel Redundancy*, in which the neighboring pixels have almost same value. Finally, *irrelevant information*, since the human visual system cannot simultaneously distinguish all colors.

Data compression a method that takes an input data D and generates the data $C(D)$ with the less number of bits as compared to input data. The reverse process is called decompression which takes the compressed data $C(D)$ and reconstructs the data D' as shown in figure 2.10. Compression can be divided into two categories, as lossless and lossy compression [28] .

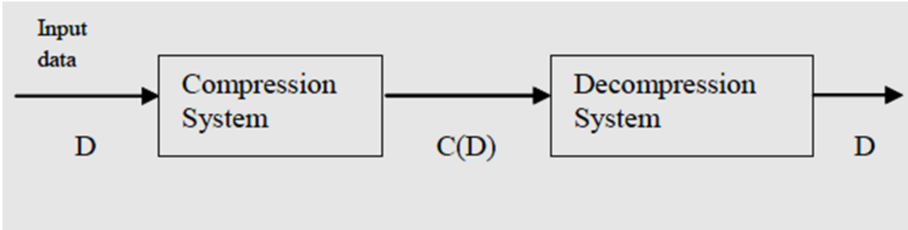

Figure 2.10: Compression-Decompression System

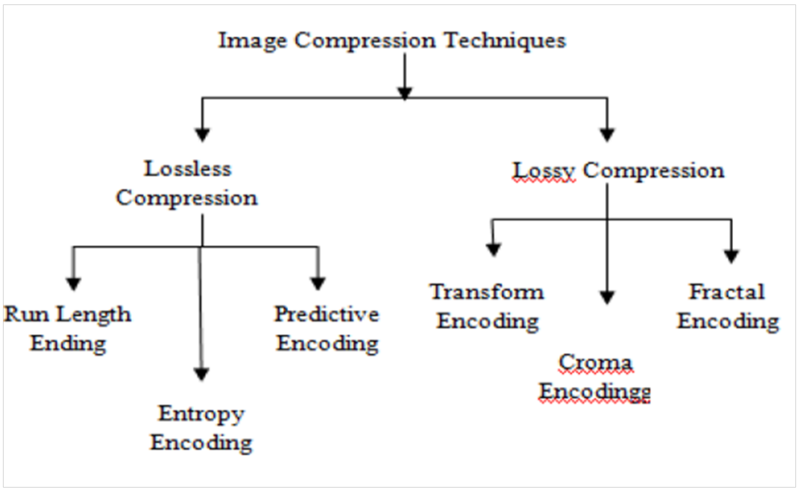

Figure 2.11: Image Compression Techniques

2.4.1 Lossless Compression Techniques

Lossless data compression techniques are applied on text data or scientific data and preferred for artificial images such as technical drawings, icons or comics. Lossless compression method may also be preferred for high value content, such as medical image scans made for archive purposes. Lossless compression is usually two steps algorithm. The first step transforms the original image to some other format in which the inter-pixel redundancy is reduced. The second step uses an entropy encoder to remove the coding redundancy. The lossless decompression is a perfect inverse process of the lossless compressor.

2.4.2 Lossy Compression Technique

Lossy method is especially suitable for natural images such photos in applications where minor loss of fidelity is acceptable to achieve a substantial reduction in bit rate. The lossy compression that produces imperceptible differences can be called visually lossless. Generally, most lossy compression is there steps algorithm. The first stage is a transform to eliminate the inter-

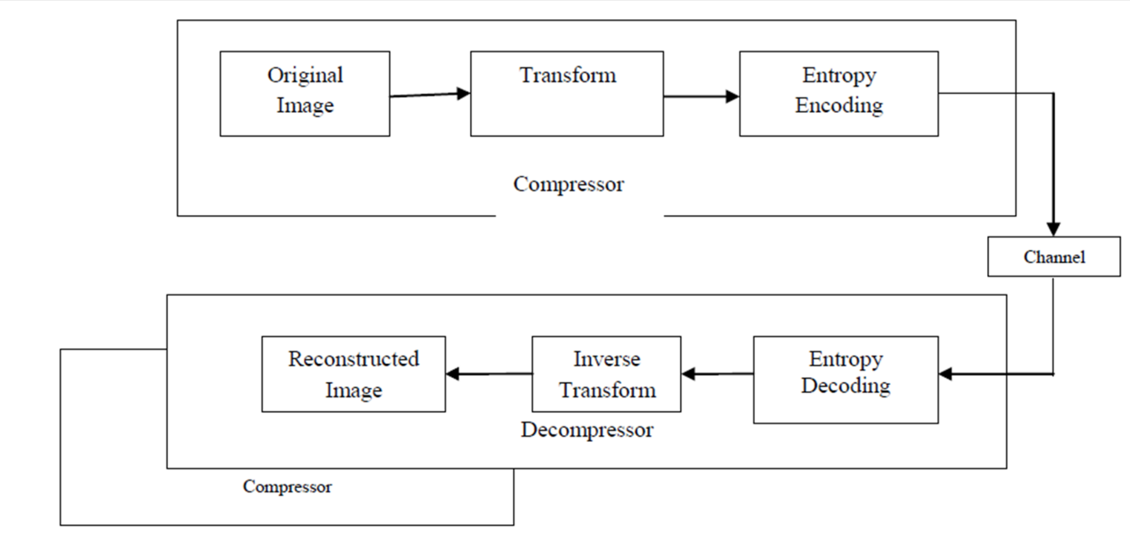

Figure 2.12: Lossless Compression Techniques

Figure 2.13: Lossless Compression Techniques

pixel redundancy to pack information efficiently. There quantizer is applied to remove psycho-visual redundancy to represent the packed information with a few bits as possible. The quantized bits are then efficiently encoded to get more compression from the coding redundancy.

Table 2.1: Image formats and its features

Format	Features	Disadvantages
TIFF (Tagged Image File Format) (lossy and lossless)	Flexible format, save 8 or 16 bits per color (RGB) totally 24 or 48 bits	Not used in web pages because TIFF files require large size.
GIF (Graphics Interchange Format)	Grayscale and black white Image, it works with 8 bits per pixel or less which indicates 256 or less colors. It states simple graphics, logos and cartoon style image.	It does not work with color
PNG (Portable Network Graphics) (Lossless)	Same 8 bits, 24 bits and 48 bits per pixel. 10 to 30% compressed than GIF format. Also, PNG format have smaller size and more colors compare to others	
JPEG (Joint Photographic Expert Group) (Lossy)	It support 8 bits gray scale and 24 bits color images, provide motion video compression, compress the meal would subjects, photographs and video stills	Black & white documents, line art animations
BMP (Bitmap) (do not compress)	Graphics file related to Microsoft window operating system, simplicity. BMP images are binary files.	Large in size, it does not support true colors
RAW (lossless/lossy)	File size smaller than TIFF format. Available on digital cameras	These are not standardized image and it require manufacture's software to

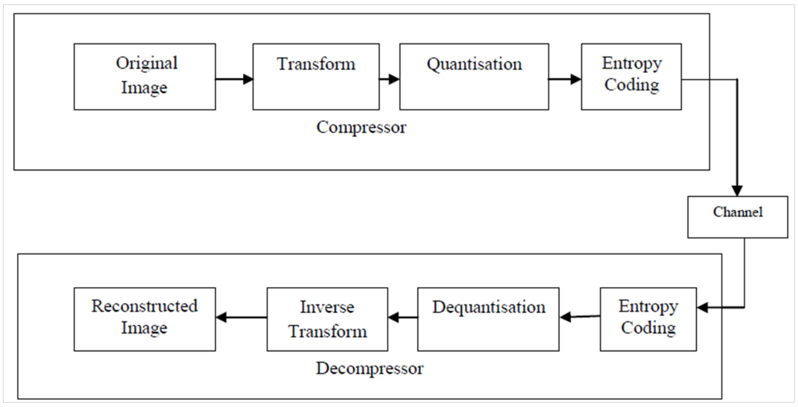

Figure 2.14: Lossy Image Compression

Figure 2.15: original Lena image (b) compressed 85% (1.8kb)(c) high compressed 96% (0.56 kb)

2.4.3 Advantage Of Image Compression

There are the following advantages of image compression. The *size reduction* is most significant benefit of the image compression. It takes up less space on the hard drive and retains the same physical size, unless edit the image's physical size in an image editor. The file size reduction with the help of internet, to create image rich sites without using much bandwidth or storage space. The second advantage is associated with data loss. Some common files like JPEG, which an image shrinks in the size of compression, will discard some of the photo's data permanently. So compress the images to ensure that decompressed back up before starting. Otherwise lose the high quality of the original decompressed image permanently. The third advantage is concerned with slow devices. Various electronics devices may load large compressed image slowly. For example CD devices can only read data at a specific rate and cannot display large images in real time. Also doe some webhost that transfer data slowly compressed images remain necessary for a fully functional websites. Image compression allow for the faster loading of data on slower devices.

2.4.4 Performance Parameters

There are two performance parameters which are used to measure the performance of the image compression algorithm. One is PSNR (Peak Signal to Noise Ratio) and second is MSE (Mean square error). The MSE is the cumulative difference between the compressed image and original image.

$$\mathrm{MSE} = \frac{\sum_{M,N} \left(L_1(m,n) - L_2(m,n)\right)^2}{M \times N} \tag{2.6}$$

PSNR is the measurement of the peak error between the compressed image and original image. The higher PSNR contains better quality of image. To complete the PSNR, first of all MSE is completed [8].

$$\mathrm{PSNR} = 10 \log_{10} \frac{R^2}{\mathrm{MSE}}, \tag{2.7}$$

where R is the relative data redundancy of the representation with b bits, which is given by

$$R = \frac{1}{c}, \tag{2.8}$$

where c is the compression ration, which is given by

$$c = \frac{\text{compressed image}}{\text{original image}} \tag{2.9}$$

This Thesis constitutes the idea of image compression, numerous technologies, different types of images used within the photo compression. All the image compression techniques are useful in their related areas and every day new compression techniques is developing which gives better compression ratio. Based or different technology, the quality of image can be measured by various important parameters like compression ratio, MSE, PSNR.

3 Chapter Three The Wavelet Transform

3.1 Introduction to Wavelet Transform

The wavelet transform has received much attention in the last few years for its application to digital signal processing problems. The wavelet transform is useful tools since it retains spatial information while at the same time provide a division of the frequency content by employing compactly supported basis function. The wavelet decomposition methodology is that the wavelet basis functions have compact support, which means that the basis functions are non-zero only on a finite interval. In contrast, the sinusoidal basis functions of the Fourier expansion are infinite in extent.

The compact support of the wavelet basis functions allows the wavelet transformation to efficiently represent functions or signals which have localized features. Many real-world signals have these features, and decompositions such as the Fourier transform are not well suited to represent such signals. The wavelet transform divides the plane into different sized bins, which gives better resolution in time for high frequency components and better frequency resolution for low frequency components (see Figure3.1).

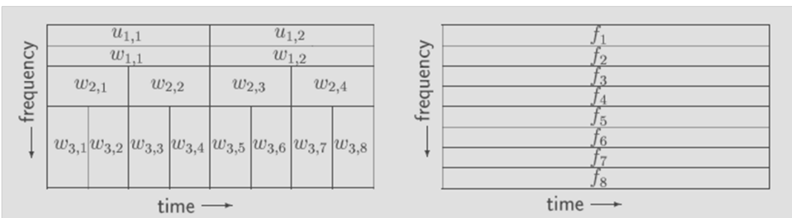

Figure 3.1: Time-frequency tiling for DWT

3.1.1 Time-frequency tiling for DWT

The DWT basis functions corresponding to the fine scale wavelet coefficients $w_{3,1}, w_{3,2}, \ldots, w_{3,8}$ are well-localized in time but have large bandwidths. They capture the high-frequency characteristics of a signal at different times. The DWT basis functions corresponding to the coarser scales wavelet coefficients $w_{2,1}, \ldots, w_{2,4}$ and $w_{1,1}$ and $w_{1,2}$, capture the intermediate frequency characteristics of the signal at different times [29].

3.1.2 Time-frequency tiling for DFT

In contrast to the DWT basis functions, the DFT basis function have supported over the entire time domain but are perfectly localized in frequency. The DFT coefficients capture the overall signal energy at a particular frequency f_n.

To develop the wavelet transform, we start with the complete signal space (function space) V_0. We will create a smoother space V_1 which is an approximation to complete signal space [29].

Signals in space are approximation of those in , lacking the fine scale structure which we have removed, therefore, we will call these spaces approximation space. Continuing this iteration upon , we have a set of nested approximation spaces to with the relationship as shown in figure3.2

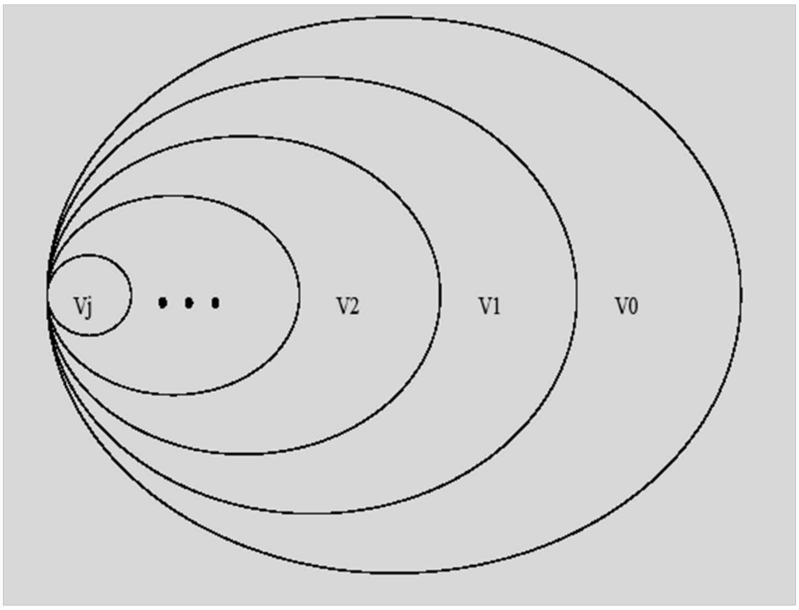

Figure 3.2: The approximation spaces

Given that each of the V_j as a subspace of the space above, we can now construct a space detail, which was removed as the orthogonal compliment to the approximation space. We can divide each V_j into the sum of two spaces as

$$V_j = V_{j+1} \oplus W_{j+1}, \tag{3.1}$$

where the operation $\oplus$ denotes direct addition and thus the space W_{j+1} is the compliment space to V_{j+1} in the space V_j. A space that is particularly important in signal processing is call $L^2(R)$. This is the space of all basis functions $f(t)$ with a well defined integral of the square of the modulus of the function. The L signifies a Lebesque integral, the "2" denotes the integral of the square of the modulus of function, and R states that the independent variable of the integration (t) is a number over the whole real line. In order to develop the wavelet expansion [14], we need the idea of an expansion set or a basis set. If we start with the vector space of signals, V_0, then if any $f(t) \in V_0$ can be expressed as

$$f(t) = \sum_k a_k \psi_k(t) \quad \text{for any} \quad f(t) \in V_0 \tag{3.2}$$

where a_k denote the expansion coefficients, and $\psi_k(t)$ called the expansion set. Then the coefficients can be calculated by the inner product

$$a_k = \Big\langle f(t), \psi(t) \Big\rangle = \int f(t)\, \psi(t)\, dt \tag{3.3}$$

We can define the wavelets as a family of functions generated from a single function by translation and dilation. The general form of these wavelets is described by

$$\psi_{j,k} = 2^{j/2}\, \psi\left(2^j t - k\right) \tag{3.4}$$

where ψ expansion set and also called *the mother wavelet* and it is used to generate all other members of the family. 2^j is the scaling of t (j is the $\log_2$ of the scale), k is the translation in t, and $2^{j/2}$ maintains the L^2 norm of the wavelet at different scales.

These wavelets are used in the wavelet transform. The purpose of the wavelet transform is to represent a signal, $f(t)$ as a superposition of wavelets.

For special choices of the signal can be represented as

$$f(t) = \sum_{j,k} c_{j,k}\, \psi_{j,k}(t) \tag{3.5}$$

$$c_{j,k} = 2^{-j/2} \int f(t)\, \psi_{j,k}\, dt \tag{3.6}$$

The purpose of obtaining this description is that it provides a representation of the signal $f(t)$ in terms of both space and frequency localization in figure3.2 . In comparison, the Fourier transform is excellent at providing a description of the frequency content of a signal. But if the signal is non-stationary the frequency characteristics vary in space, which is in different regions the signal $f(t)$ may exhibit very different frequency characteristics, the Fourier transform does not take this into account. The wavelet transform on the other hand produces a representation that provides information on both the frequency and time characteristics and where these characteristics are localized in space. The coefficients $c_{j,k}$ characterize the projection of f onto the base formed by (j, k). For different j represents different frequency characteristics, k is the translation of the dilated mother wavelet, therefore $c_{j,k}$ represent the combined space-frequency characteristics of the signal. The $c_{j,k}$ are called *wavelet coefficients*.

3.2 2D Discrete wavelet transform

The two-dimensional (2D) discrete wavelet transform (DWT) represents an image $x(t) \in L^2(R^2)$ in the terms of a set of shifted and dilated wavelet functions $\left\{\psi^{LH}, \psi^{HL}, \psi^{HH}\right\}$ and scaling function ϕ^{LL}. When these shifted and dilated functions form an othonormal basis for $L^2\left(R^2\right)$, the image can be decomposed as

$$x(t) = \sum_{k \in Z^2} u_{j,k}\, \phi^{LL}_{j,k}(t) + \sum_{b \in B} \sum_{k \in Z^2} w^b_{j,k}\, \psi^b_{j,k}(t) \tag{3.7}$$

where

$$\phi^{LL}_{j,k} = 2^j \phi^{LL}\left(2^j t - k\right), \tag{3.8}$$

$$\psi^b_{j,k} = 2^j \psi^b\left(2^j t - k\right), \tag{3.9}$$

and finally

$$b \in B = \{LH, HL, HH\}. \tag{3.10}$$

The values LH, HL, HH denote the sub bands of the wavelet decomposition. The expansion coefficients, called the scaling coefficients and wavelet coefficients, which are given by

$$u_{j,k} = \int_{t \in R^2} x(t)\phi_{j,k}(t)\, dt, \quad \text{and} \tag{3.11}$$

$$w^b_{j,k} = \int_{t \in R^2} x(t)\psi^b_{j,k}(t)\, dt, \tag{3.12}$$

respectively.

For simplicity we will use for 2-DWT coefficients and basis functions, $w^b_{j,k} \rightarrow w_i$ and $\psi^b_{j,k} \rightarrow \psi_i$. In practice, the image will be discretized using $N \times N$ grid. This imposes a maximal level of decomposition $j = \log_2 N$ with 4^{j-1} wavelet coefficients in each subband and 4^{j-1} scaling coefficients at each scale.

3.2.1 Wavelet Transform Properties

Wavelet transforms possess a number of endearing properties that make wavelet-domain statistical image processing attractive. We will section the wavelet properties into three types; primary, secondary, and tertiary properties. The following is the primary properties of the wavelet transform [30] and [31]. WP1. Locality: The wavelet coefficient represents image content locally in space and frequency (see figure3.1).

WP2. Multi-resolution: The wavelet transform represents and analyzes the image at a nested set of scales. Four wavelets at given scale nest inside one at the next coarser scale, giving rise to quad-tree of wavelet coefficients that mirrors that dyadic squares (see Figure 3.3).

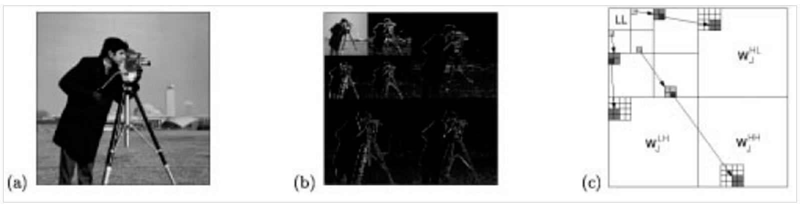

Figure 3.3: Cameraman image in WT

Figure 3.3: (a) “Cameraman” image. (b) The two-dimensional wavelet

transform represents an image in terms of (low pass) scaling coefficients and three sub bands of (band pass) wavelet coefficients that detect edges in the horizontal (LH), vertical (HL), and diagonal directions (HH). (c) The wavelet sub bands form three multi scale quad-trees, with each (parent) coefficient having four child coefficients in the next finer scale band. The child wavelets divide the support of the parent wavelet in four.

WP3. Edge Detection: Wavelets act as local edge detectors. The edges in the image are represented by large wavelet coefficients at the corresponding locations.

WP4. Energy Compaction: The wavelet transforms of real-world images tend to be sparse. A wavelet coefficient is large only if edges are present within the support of the corresponding wavelet filter.

WP5. Decorrelation: The wavelet coefficients of real-world images tend to be approximately de-correlated. The primary properties give the wavelet coefficients of natural images significant statistical structure, which leads us to the following secondary properties [30].

WS1. Non-Gaussianity: The wavelet coefficients have peaky, heavy-tailed marginal distributions [30]. The Energy Compaction (WP4) of the signal in the wavelet domain results in non Gaussian marginal probability density of the wavelet coefficients as shown in Figure 3.4. Which can be understood as; The Gaussian component corresponding to the small state has a relatively small variance, capturing the peakiness around zero, while the component corresponding to the large state has a relatively large variance, capturing the heavy tails. Even though, no Gaussian density has heavy tails in the strict sense. But you find that a Gaussian with a large variance captures the shape of the heavy-tailed density in the region where large values are likely.

WS2. Persistency: Large/small values of wavelet coefficients tend to propagate through the scales of the quad-trees [5]. Persistency is an effect of the Edge Detection (WP3) and Multi-resolution (WP2) properties. (See Figure3.5

respectively, in Donoho and Johnstone's (a) Doppler and (b) Bumps test

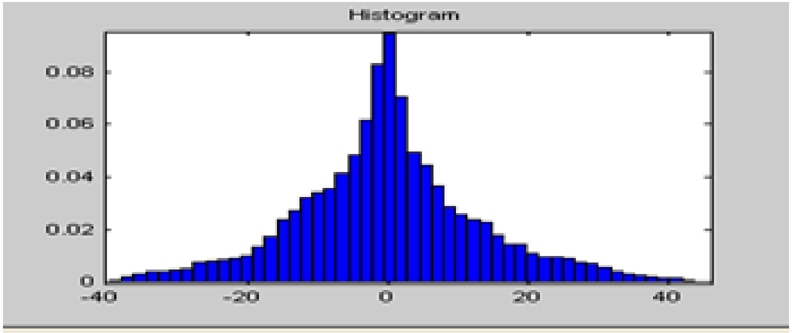

Figure 3.4: Peaky and heavy-tailed marginal histogram of the finest scale (J=5) wavelet coefficients of cameraman image.

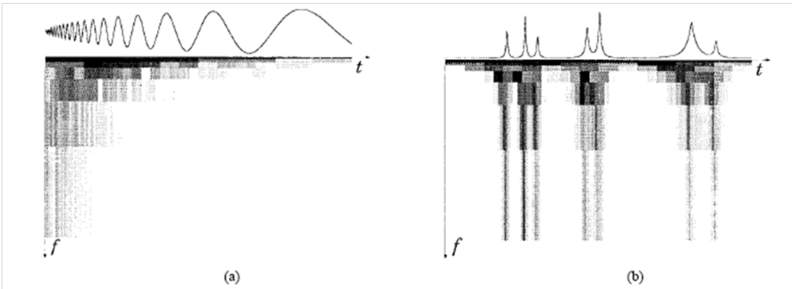

Figure 3.5: Clustering and persistence illustrated

signals [1]. The signals lie atop the time–frequency tiling (Fig.3-1) provided by a seven-scale wavelet transform. Each tile is colored as a monotonic function of the wavelet coefficient energy,with darker tiles indicating greater energy. An additional wavelet-domain properties exploited by the HMT can be use to reduce HMT model parameters. This model is constructed using two empirical tertiary properties of image wavelet coefficients. These tertiary properties reflect the self-similar nature of images and their resulting generalized $1/f$ spectral behavior [2].

WT1. Exponential decay across scale: The magnitudes of the wavelet coefficients of real-world images decay exponentially across scale.

WT2. Stronger persistence at fine scales: The persistence of large/small wavelet coefficient magnitudes becomes exponentially stronger at finer scales. Using WT1 and WT2, we will develop a reduced-parameter HMT model that is described with just nine meta-parameters independent of the size of the image and the number of wavelet scales.

3.3 JPEG 2000 Image Compression

3.3.1 Introduction

The JPEG (Joint Photographic Experts Group) 2000 standard, finalized in 2001, defines a new image coding scheme using state of the art compression techniques based on wavelet technology. Its architecture is useful for many diverse applications, including Internet image distribution, security systems, digital photography, and medical imaging. A lot of confusion exists as to what JPEG 2000 is and how it compares with other compression standards such as MPEG (Moving-Picture Experts Group) -2, MPEG-4, and the earlier JPEG. With brief comparisons to other compression standards, this article is primarily intended to highlight some of the often misunderstood and rarely mentioned potential-become-actual benefits of JPEG 2000. JPEG 2000 is a Compression techniques are used to reduce the redundant information in the image data in order to facilitate the storage, transmission and distribution of images (e.g. GIF, TIFF, PNG, JPEG) [31].

3.3.2 Features of JPEG 2000

• Lossless and lossy compression: the standard provides lossy compression with a superior performance at low bit-rates. It also provides lossless compression with progressive decoding. Applications such as digital libraries/-databases and medical imagery can benefit from this feature.
• Protective image security: the open architecture of the JPEG2000 standard makes easy the use of protection techniques of digital images such as watermarking, labeling, stamping or encryption
• Region-of-interest coding: in this mode, regions of interest (ROI's) can be defined. These ROI' scan be encoded and transmitted with better quality than the rest of the image.
• Robustness to bit errors: the standard incorporate a set of error resilient tools to make the bit-stream more robust to transmission errors. Example of region of interest coding shown in the following figure A region of interest in the Barbara image is reconstructed with quality scalability. The region of interest is decoded first before any background information.

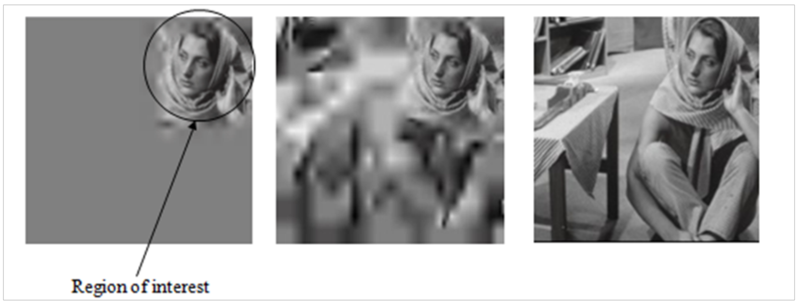

Figure 3.6: JPEG 2000 example of Region of interest

3.3.3 Limitations of JPEG Standard

- Low bit-rate compression

JPEG offers an excellent quality at high and mid bit-rates. However, the quality is unacceptable at low bit-rates (e.g. below 0.25 bpp) • Lossless and lossy compression

JPEG cannot provide a superior performance at lossless and lossy compression in a single code-stream. • Transmission in noisy environments

the current JPEG standard provides some resynchronization markers, but the quality still degrades when bit-errors are encountered. • Different types of still images

JPEG was optimized for natural images. Its performance on computer generated images and bi-level (text) images is poor.

3.3.4 JPEG 2000's Advantages Over Other Compression Standards

All MPEG standards are complex and computation intensive. This translates into extensive processing latency and memory requirements in standard- definition (SD) applications. These factors become even more of a problem when high-definition (HD) formats are considered, and JPEG 2000 becomes even more desirable. Another strength of JPEG 2000 is the standard itself, which allows immense flexibility and control in many different applications. There is also much versatility regarding formats: JPEG 2000 supports anything from 8-bits per sample to an unlimited amount of bits per sample, whereas MPEG only supports 8-bit data. JPEG 2000 continues to gain popularity, even though MPEG-2 is the established standard for DVD and broadcast applications. JPEG 2000 is also very popular in HD applications that require high-quality storage or transmission of HD images over wireless or other links.

3.3.5 DCT versus WT

JPEG 2000 uses the wavelet transform (WT) to reduce the amount of information contained in a picture, while MPEG and JPEG systems use the discrete cosine transform (DCT). It is true that the WT requires more processing power than the DCT, but MPEG systems require more than just the DCT. The DCT, or any type of Fourier transform, expresses the signal in terms of frequency and amplitude—but only at a single instant in time. The WT transforms a signal into frequency and amplitude over time, and is therefore more efficient. The figures on the following page demonstrate this. To obtain the same amount of information as with one WT pass, the DCT must be used for every frequency; and each of these frequencies must be transformed at each time instant for each (8*8) pixel block. In addition, MPEG systems use inter-frame compression [motion estimation] in order to reduce the amount of data further for motion estimation. This requires storage of at least two entire fields in external memory. The computation-intensive motion estimation process requires a very powerful processor. Temporal compression can be used in JPEG 2000 systems, but it is not inherent in the JPEG 2000 standard.

3.3.6 Applications of JPEG2000

CCTV Security
When transmitting or storing picture information, compression must be employed to maintain picture resolution while making best use of limited channel bandwidth. Compression is defined as lossless if full recovery of the original is available from the channel without any loss of information; otherwise, it is lossy. Standards are required to ensure interoperability. JPEG 2000 is the only standard compression scheme that provides for both lossless and lossy compression . As such, it lends itself to applications that require high-quality images despite limitations on storage or transmission bandwidths. An important feature of systems based on JPEG 2000 is the ability to extract a variety of resolutions, components, areas of interest, and compression ratios from a single JPEG 2000 code stream. This is not possible with any other compression standard because the image size, bit rate, and quality must be specified

on the encode side and can not be determined or changed on the decode side. For example, a closed- circuit TV (CCTV) security system can make use of this feature by sending a single JPEG 2000 code stream over a low bandwidth network. High-resolution images can be stored on a hard- disk drive (HDD), while several lower-resolution images are displayed on monitors. The operator on the receive side can decide what information to extract from the single code stream sent [31]. JPEG 2000 is frame accurate, in that every single frame of the input is contained in the compressed format. MPEG systems, on the other hand, reduce the amount of data through temporal compression (which does not encode each frame as a complete image), so MPEG compression is not frame-accurate. For this reason, legal issues restrict the use of MPEG compression in some security applications. To get around this problem, security system and equipment providers have had to develop their own compression schemes—or use the highly inefficient motion JPEG (M-JPEG) compression standard—in order to provide a compressed stream that contains every single field of the original. They can now use JPEG 2000 for new designs [10].

Internet Image Distribution

Progressive coding, another feature of the JPEG 2000 standard, means that the bit stream can be coded in such a way as to contain less-detailed information at the beginning of the stream and more detailed information as the stream progresses. This makes it ideal for Internet/network applications—especially with large images and low bandwidths—as the image can be seen instantly on the decoding side, even with low-speed networks or image databases. The lower sub bands are shown first, and more detail is added as time progresses. The picture thus becomes sharper and more detailed over time, and the entire image does not have to be downloaded before it can be seen [32]. With the low-quality image instantly available, the user at the receiving end can decide whether to view the picture in its fully decoded version, or to pass it by and scan the next picture instead. Clients can view images at different resolutions or quality levels [compression rates] making them suitable for any transmission bandwidth, connection speed, or display device. In addition, JPEG 2000 coding provides the option to zoom in or out on a particular area of the image—or to display a particular region of the image at a different resolution or compression rate. High Definition

At extreme compression levels, JPEG 2000 video starts to blur, but is still quite viewable. MPEG or JPEG artifacts are much more disturbing to the eye, with the picture visibly broken down into small blocks at high compression ratios. The high image quality at medium-to-high bit rates and contents that contain a lot of motion, lack of block artifacts, and high efficiency make JPEG 2000 ideal for high-definition (HD) applications, such as digital cinema, HD recording systems, and HD camera equipment. Many applications require exact bit-rate control, which only JPEG 2000 can provide. Exact bit-rate control is possible because an entire frame or field is transformed at once; it is then broken down into bit streams or code blocks that can be processed independently with the techniques described below. In systems using DCT, quantization is the only technique used, and this makes exact bit-rate control difficult. In order to control bit rate in DCT systems, the information must be repeatedly re-processed and re-quantized. The rate- control algorithm used in JPEG 2000 truncates each bit stream to meet a specific target bit rate, adjusting the truncation and re-quantization of each code block's data as required. In addition to programming the target bit rate, the standard allows the user to specify a particular quality metric. In this case, the target bit rate will vary to meet the specified quality factor, as long as the performance does not fall below a specific peak signal-to-noise ratio. The PSNR is an indication of picture quality comparable to perceived picture quality [9]

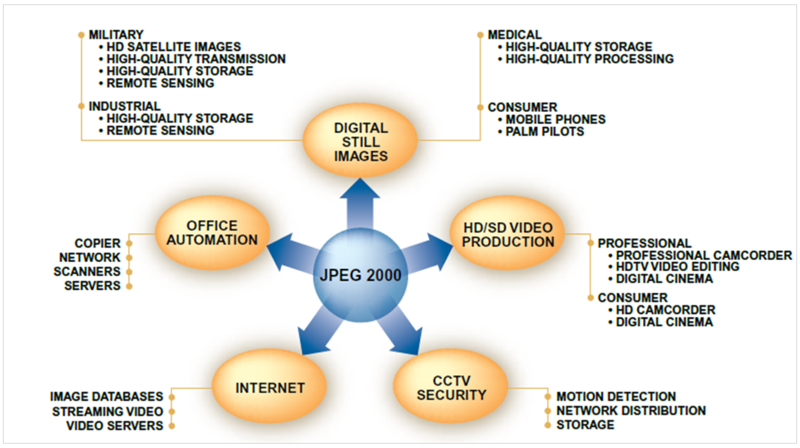

Figure 3.7: JPEG 2000 applications

3.3.7 JPEG 2000 Code Stream

A given input image or part of the image [tile] is sent to a set of wavelet filters, which transform the pixel information into wavelet coefficients, which are then grouped into several sub bands [the use of wavelets in encoding was first explained in Analog Dialogue 30 -2 (1996)]. Each sub band contains wavelet coefficients that describe a specific horizontal and vertical spatial frequency range of the entire original image. This means that lower-frequency, less-detailed information is contained in the first transform level, while more - detailed, higher-frequency information is contained in higher transform levels. For simplicity, only two levels of transform are shown here. The first transform level results in sub bands LH1, HH1, HL1, and LL1. Only sub band LL1 is passed on for further filtering, generating the next transform level and creating sub bands LH2, HH2, HL2, and LL2. Equally sized code blocks, which are essentially bit streams of data, are generated within each sub band. This break-down is necessary for coefficient modeling and coding, and is done on a code-block-by-code-block basis. In essence, the actual compression is achieved by truncating and/or re-quantizing the bit streams contained in each code block. These bit streams are then optimally truncated using a technique knows as post-compression-rate-control (PCRC). Code blocks can be accessed independently. Their bit streams are coded with three coding passes per bit plane. This process, called context modeling, is used to assign information about the importance of each individual coefficient bit. The code blocks can then be grouped according to their significance. On the decoding side it is then possible to extract information according to its significance, allowing the most significant information to be seen first. JPEG 2000 can contain a user-defined number of layers, which are defined by PCRC and context modeling. Each layer stands for a particular compression rate, where the compression rate is achieved from the quantization-, rate-distortion-, and context modeling processes. Layer 0, for example, contains bit streams-from the lossy WT transform-that are heavily truncated, contain no coding passes, and thus provide the highest compression rate and the lowest quality. Layer 16 can then contain bit streams that are less truncated and use a higher number of coding passes, thus providing low compression and high quality [16]. Tiles or images are further partitioned into precincts. Precincts contain a number of code blocks, and are used to facilitate access to a specific area within an image in order to process this area in a different way, or to decode only a specific area of an image. The JPEG 2000 bit stream is generated by arranging code blocks or precincts into an array of packets with the lower subbands coming first. The JPEG 2000 stream starts with a main header containing information such as: uncompressed image size, tile size, number of components, bit depth of components, coding style, transform levels, progression order, number of layers, code block size, wavelet filter type, quantization level, etc. The entire image data, grouped in code blocks of LL, HL, LH, and HH subbands, follows the header. Data is not contained in the header information. Also, a table of contents can be stored on the encode side, and allows a decoder to call up a certain resolution on demand, without first having to decode or download the entire JPEG 2000 code stream [16].

3.3.8 Encoder and Decoder Structures of JPEG-2000

The simplified structures of the encoder and decoder of JPEG-2000 are shown in Figure 3.8 Assume that we have a multiple-component image. The major processing steps of the encoder are: component transformation, tiling, wavelet transformation, quantization, coefficient bit modeling, arithmetic coding, and rate-distortion optimization. The role of the decoder is to reverse the steps performed by the encoder, except the rate-distortion optimization step.

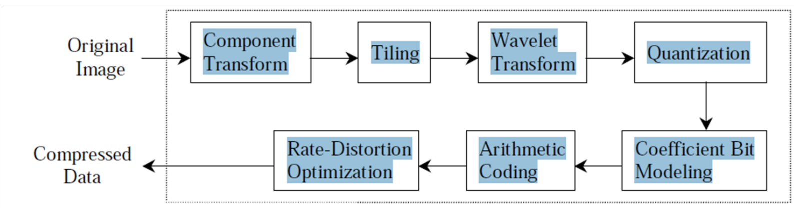

Figure 3.8: Encoder Processing Steps

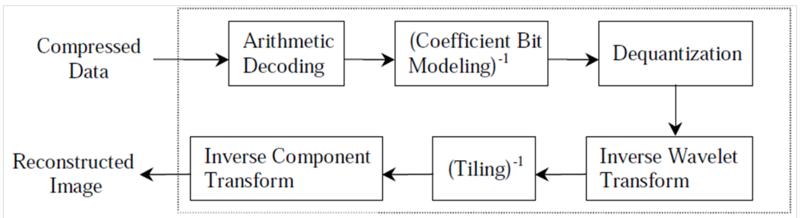

Figure 3.9: Encoder and decoder structure of JPEG-2000

3.3.9 Compression In the Encoder

Component Transform(Three steps:)

- Image tiling (optional) for each image component
- DC level shifting to samples of each tile are subtracted the same quantity (i.e. component depth). • Color transformation (optional) from RGB to Y,

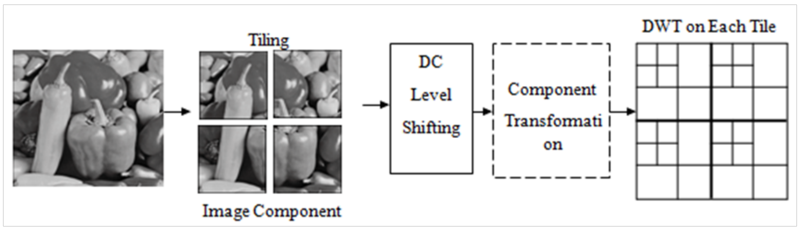

Figure 3.10: Image Tiling and process in encoder

Cb and Cr • Discrete Wavelet Transform (DWT) is used to decompose each tile component into different sub-bands.

• The transform is in the form of dyadic decomposition and use bi- orthogonal wavelets.

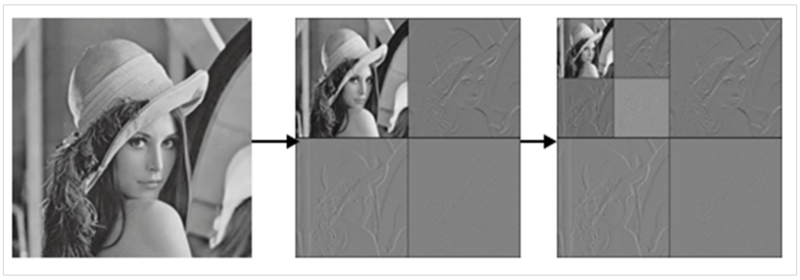

Figure 3.11: Forward dwt transform

DWT can be irreversible or reversible Although Two filtering modes are supported

- Convolution based
- Lifting based

. (2D)-Forward Transform

• 1-D sets of samples are decomposed into low-pass and high-pass samples.

• Low-pass samples represent a down-sampled, low resolution version of the original set. • High pass samples represent a down-sampled residual version of the original set (details).

3.3.9.1 Quantization

After transformation, all coefficients are quantized using scalar quantization. Quantization reduces coefficients in precision. The operation is lossy unless the quantization step is 1 and the coefficients integers (e.g. reversible integer

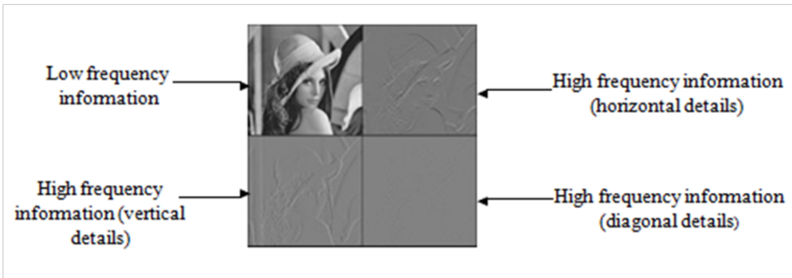

Figure 3.12: Forward dwt transform with details

5/3 wavelet). The process follows the formula

$$q_b(u,v) = \text{sign}\big(a_b(u,v)\big)\,\frac{a_b(u,v)}{\Delta_b} \tag{3.13}$$

where q_b is the quantization level, (u, v) is the transform coefficient of sub band Δ_b=quantization step,a_b (u, v)=largest integer not exceedinga_b Modes of Quantization

Integer mode€ integer-to-integer transforms are employed. Quantization step are fixed to one. Lossy coding is still achieved by discarding bit-planes.

Real mode€ real-to-real transforms are employed. Quantization steps are chosen in conjunction with rate control. In this mode, lossy compression is achieved by discarding bi-planes or changing the size of the quantization step or both.

- Precinct: each sub-band is divided into rectangular blocks called precincts.
- Packets: three spatially consistent rectangles comprise a packet.
- Code-block: each precinct is further divided into non-overlapping rectangles called code-blocks.
- Each code-block forms the input to the entropy encoder and is encoded independently.
- Within a packet, code-blocks are visited in raster order.

Entropy Coding: Bit-planes

- The coefficients in a code block are separated into bit-planes. The individual bit-planes are coded in 1-3 coding passes. Entropy Coding: Coding Passes Each of these coding passes collects contextual information about the bit- plane data. The contextual information along with the bit-planes are used by the arithmetic encoder to generate the compressed bit-stream. The coding passes are:

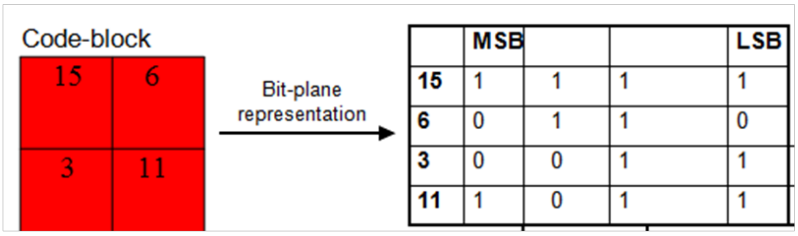

Figure 3.13: Bit-planes (Entropy Coding)

• Significance propagation pass € coefficients that are insignificant and have a certain preferred neighborhood are coded.
• Magnitude refinement pass € the current bits of significant coefficients are coded. • Clean-up pass € the remaining insignificant coefficients for which no information has yet been coded are coded.
JPEG2000 Bit-stream
For each code-block, a separate bit-stream is generated . The coded data of each code-block is included in a packet. If more that one layer is used to encode the image information, the code-block bit-streams are distributed across different packets corresponding to different layers.

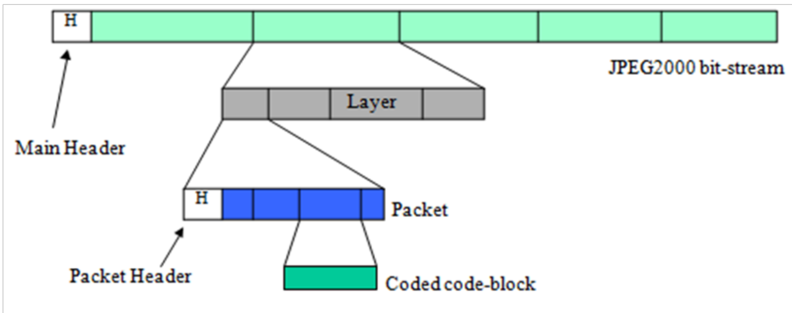

Figure 3.14: JPEG 2000 bit stream

For a 512 x 512 gray-level image compressed with one tile, code-block size 64 x 64, precinct size 512 x 512, 3 levels of decomposition and one layer, the general structure of the bit stream is as follows If all the packet headers are

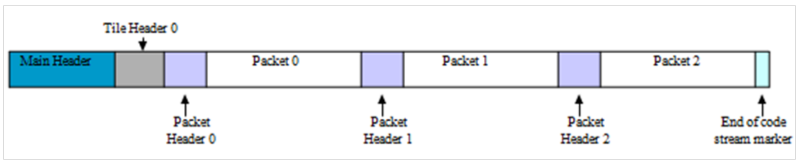

Figure 3.15: JPEG 2000 bit stream example

grouped together in a single header and placed in the main header, the structure is Layers of the JPEG2000 Bit-stream

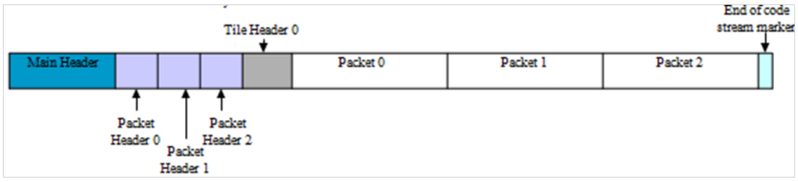

Figure 3.16: JPEG 2000 bit stream example (packet together)

Therefore, each layer consists of a number of consecutive bit-plane coding passes from each code-block in the tile, including all sub-bands of all components for that tile. Layer Formation

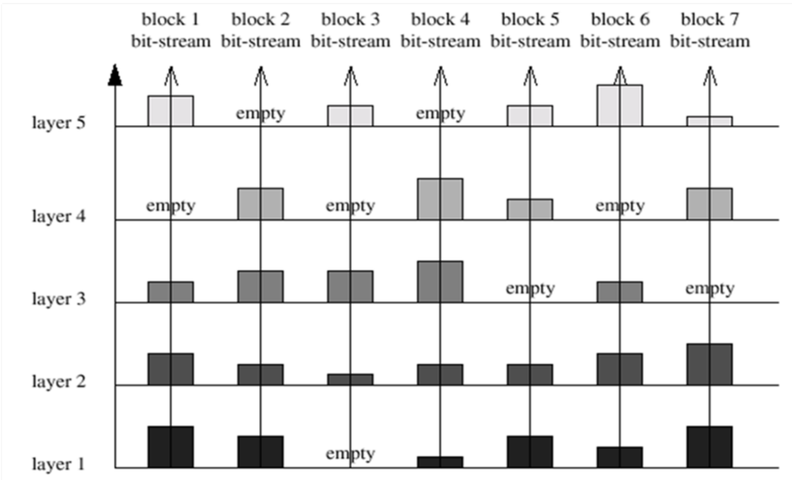

Figure 3.17: Layers of the JPEG2000 Bit-stream

The individual code-block streams have the property that they can be truncated to a variety of discrete lengths R1, R2, R3...Rn. . The distortion incurred when reconstructing from each of these truncated subsets is estimated and denoted by D1, D2, D3...Dn. The Mean Squared Error distortion metric is generally used. The first, lowest quality layer, is formed from the optimally truncated code-block bit-streams.

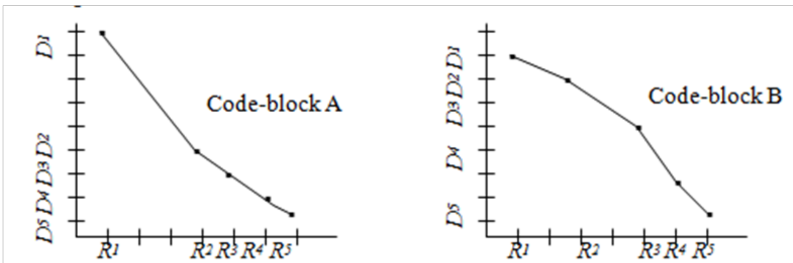

Figure 3.18: two individual code-block streams

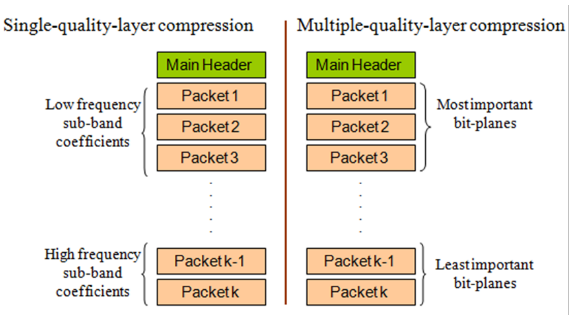

Figure 3.19: Hierarchical structure of the JPEG2000 Bit-stream

3.3.9.2 Quality Scalability

By interleaving the packets in different orders, four possible progression orders can be achieved in JPEG2000 Quality , Resolution , Spatial location and Component

Figure 3.20: The Barbara image is decompressed at different qualities

3.3.9.3 Resolution Scalability

In a resolution scalable image coding algorithm, a multiresolution representation of the data is often obtained using a linear filter bank. Reversible cellular automata have been recently proposed as simpler, nonlinear filter banks that produce a similar representation. The original image is decomposed into four subbands, such that one of them retains most of the features of the original image at a reduced scale. [21]

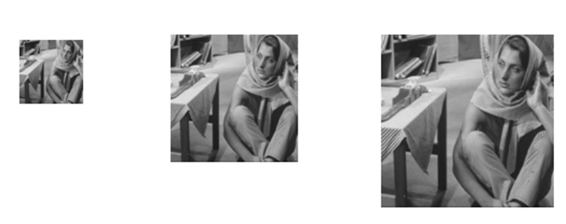

Figure 3.21: The Barbara image is decompressed at different resolution

4 Chapter Four: Results and Analysis

4.1 Image De-noising

This section takes you through the features of two-dimensional discrete wavelet analysis using the Matlab software. to provides these functions for image analysis. Although we will show how you can use two-dimensional wavelet analysis to compress an image efficiently without sacrificing its clarity in the following steps:

1. Load the Image using the command imread

2. Display the image. The oupt is shown in figure 4.1

Figure 4.1: Original color Image.

3. Convert Image to Grayscale Image

4. Perform a single-level wavelet decomposition To perform a single-level decomposition of the image using the bior2.2 wavelet Type the following code.

[cA1,cH1,cV1,cD1] = dwt2(X,'bior3.7');

Figure 4.2: Gray Scale Image

This generates the coefficient matrices of the level-one approximation (cA1) and horizontal, vertical and diagonal details (cH1,cV1,cD1, respectively).

5. Construct and display approximations and details from the coefficients. To construct the level-one approximation and details (A1, H1, V1, and D1) from the coefficients cA1, cH1, cV1, and cD1, type the follwing code.

```
A1 = upcoef2('a',cA1,'bior3.7',1);
H1 = upcoef2('h',cH1,'bior3.7',1);
V1 = upcoef2('v',cV1,'bior3.7',1);
D1 = upcoef2('d',cD1,'bior3.7',1);
```

Figure 4.3 shows the single-level wavelet decomposition. Figure 4.4 shows the level-one approximation and details.

6. Regenerate an image by single-level Inverse Wavelet Transform. To find the inverse transform, type

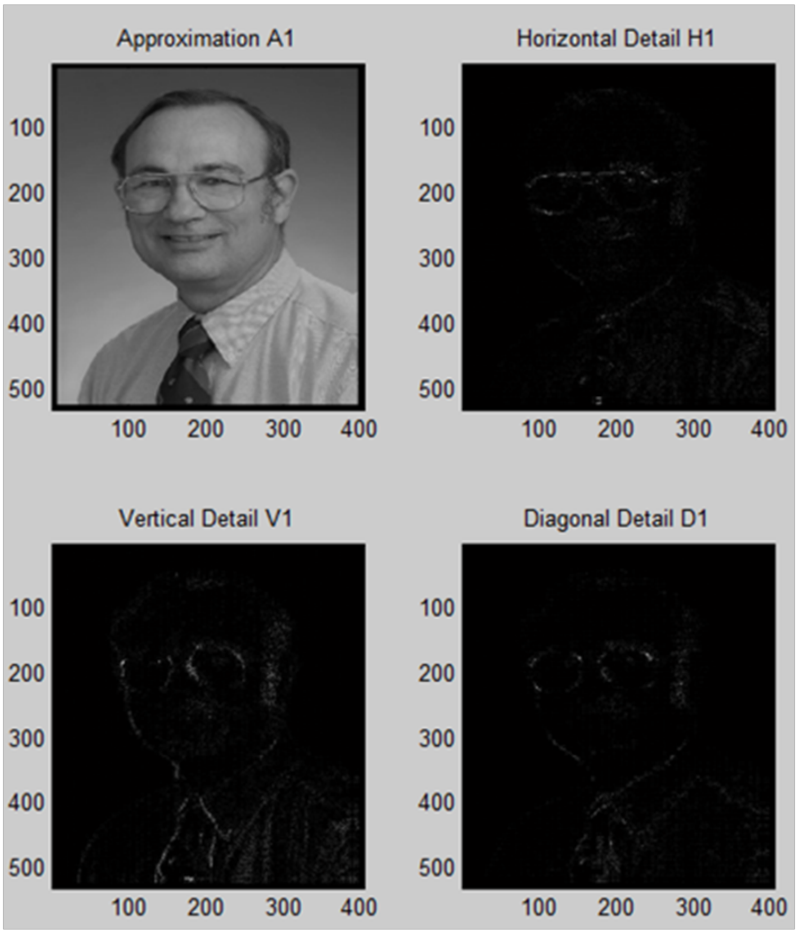

Figure 4.3: single-level wavelet decomposition

Xsyn = idwt2(cA1,cH1,cV1,cD1,'bior3.7');

7. Perform a multilevel wavelet decomposition. To perform a level 2 decomposition of the image (again using the bior3.7 wavelet), type
   [C,S] = wavedec2(X,2,'bior3.7');
   where X is the original image matrix, and 2 is the level of decomposition. The coefficients of all the components of a second-level decomposition (that is ,the second-level approximation and the first two levels of detail) are returned concatenated into one vector, C. The Argument S is a bookkeeping matrix that keeps track of the sizes of each component.

8. Extract approximation and detail coefficients. To extract the level 2 approximation coefficients from C, type
   cA2 = appcoef2(C,S,'bior3.7',2);
   To extract the first- and second-level detail coefficients from C, type

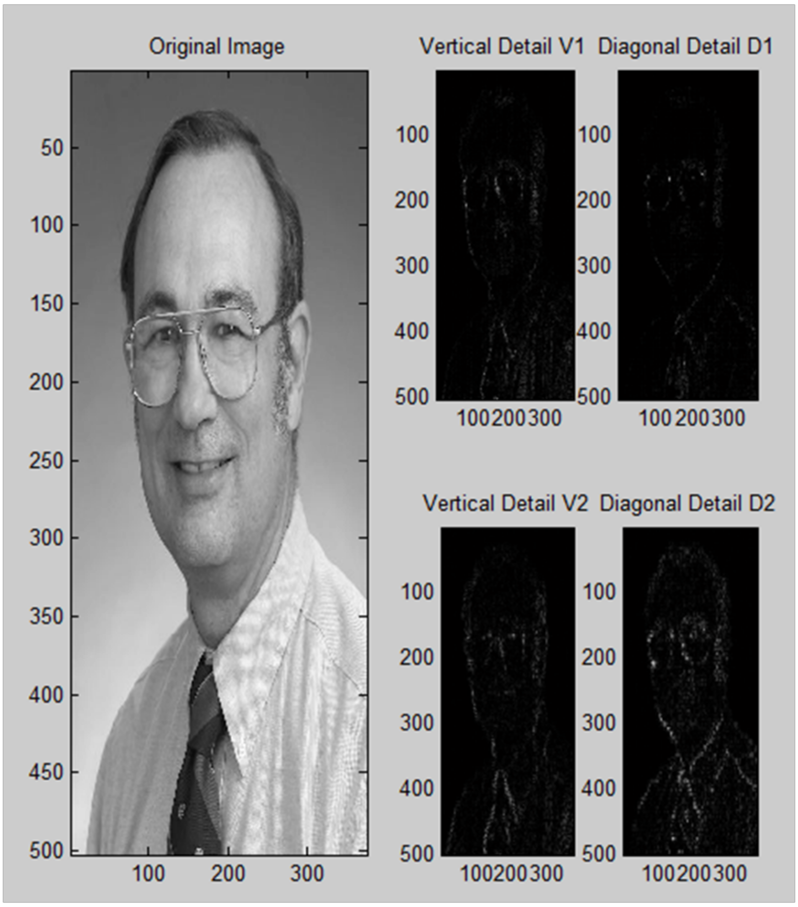

Figure 4.4: level-one approximation and details

```
[cH2,cV2,cD2] = detcoef2('all',C,S,2);
[cH1,cV1,cD1] = detcoef2('all',C,S,1);
```

where the first argument ('h', 'v', or 'd') determines the type of detail (horizontal, vertical, diagonal) extracted, and the last argument determines the level.

9. Reconstruct the Level 2 approximation and the Level 1 and 2 details. To reconstruct the level 2 approximation from C, type
   A2 = wrcoef2('a',C,S,'bior3.7',2);
   To reconstruct the level 1 and 2 details from C, type

```
H1 = wrcoef2('h',C,S,'bior3.7',1);
V1 = wrcoef2('v',C,S,'bior3.7',1);
D1 = wrcoef2('d',C,S,'bior3.7',1);
H2 = wrcoef2('h',C,S,'bior3.7',2);
```

```
V2 = wrcoef2('v',C,S,'bior3.7',2);
D2 = wrcoef2('d',C,S,'bior3.7',2);
```

10. Display the results of a multilevel decomposition. Note With all the details involved in a multilevel image decomposition, it makes sense to import the decomposition into the Wavelet 2D graphical tool in order to more easily display it. To display the results of the level 2 decomposition, type the following code. the output is shown in figure 4.5.

```
colormap (map);
subplot(2,4,1);image(wcodemat(A1,192));
title('Approximation A1')
subplot(2,4,2);image(wcodemat(H1,192));
title('Horizontal Detail H1')
subplot(2,4,3);image(wcodemat(V1,192));
title('Vertical Detail V1')
subplot(2,4,4);image(wcodemat(D1,192));
title('Diagonal Detail D1')
subplot(2,4,5);image(wcodemat(A2,192));
title('Approximation A2')
subplot(2,4,6);image(wcodemat(H2,192));
title('Horizontal Detail H2')
subplot(2,4,7);image(wcodemat(V2,192));
title('Vertical Detail V2')
subplot(2,4,8);image(wcodemat(D2,192));
title('Diagonal Detail D2')
```

11. Reconstruct the original image from the multilevel decomposition. To reconstruct the original image from the wavelet decomposition structure, type
X0 = waverec2(C,S,'bior3.7');
This reconstructs or synthesizes the original image from the coefficients C of the multilevel decomposition.

4.2 Image Compression

To compress the original image X, use the ddencmp command to calculate the default parameters and the wdencmp command to perform the actual

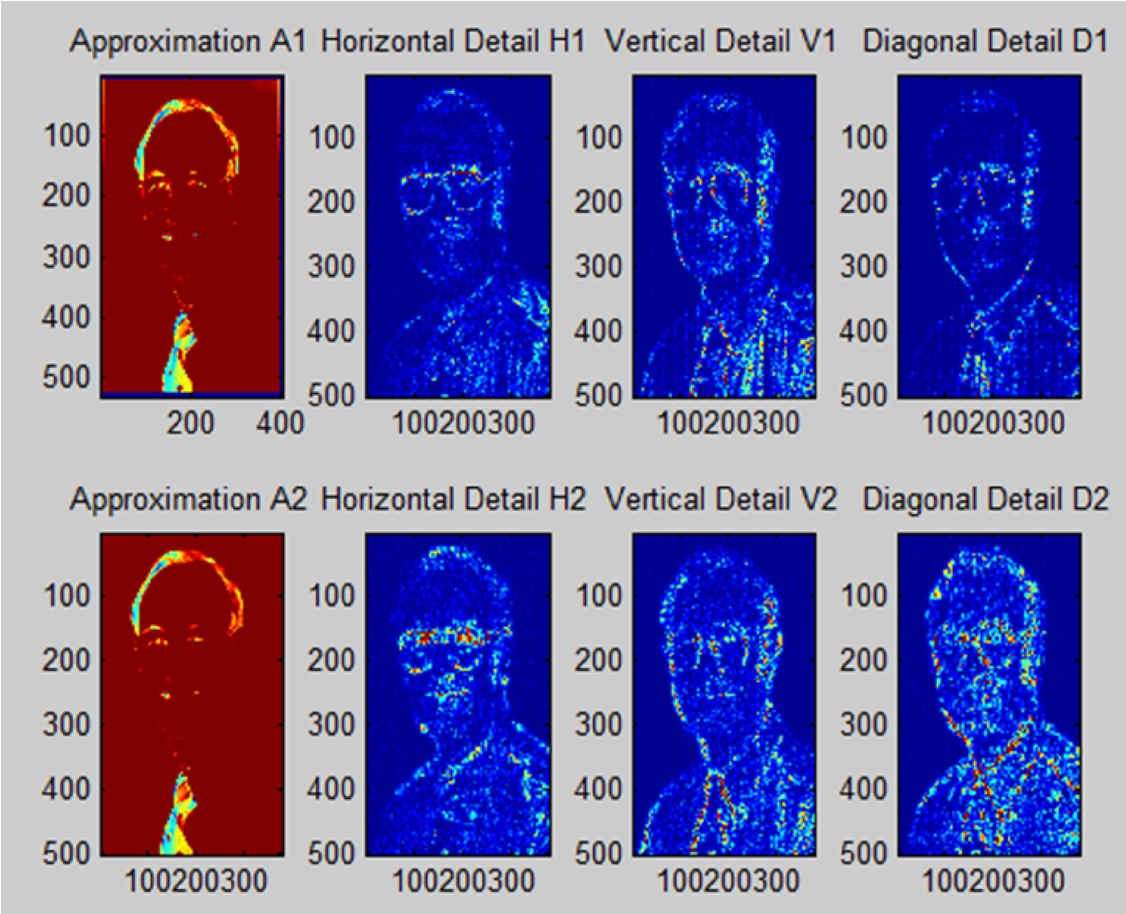

Figure 4.5: level 2 decomposition

Figure 4.6: Result of 2 level Image decomposition

compression. Type

```
[thr,sorh,keepapp]= ddencmp('cmp','wv',X);
[Xcomp,CXC,LXC,PERF0,PERFL2] = ...
wdencmp('gbl',C,S,'bior3.7',2,thr,sorh,keepapp);
```

Note that we pass in to wdencmp the results of the decomposition (C and S) we calculated in step 7. We also specify the bior3.7 wavelets, because we used this wavelet to perform the original analysis. Finally, we specify the global thresholding option 'gbl'. See ddencmp and wdencmp reference pages for more information about the use of these commands. To view the compressed image side by side with the original, type

```
colormap(map);
subplot(121); image(X); title('Original Image');
axis square
subplot(122); image(Xcomp); title('Compressed Image');
```

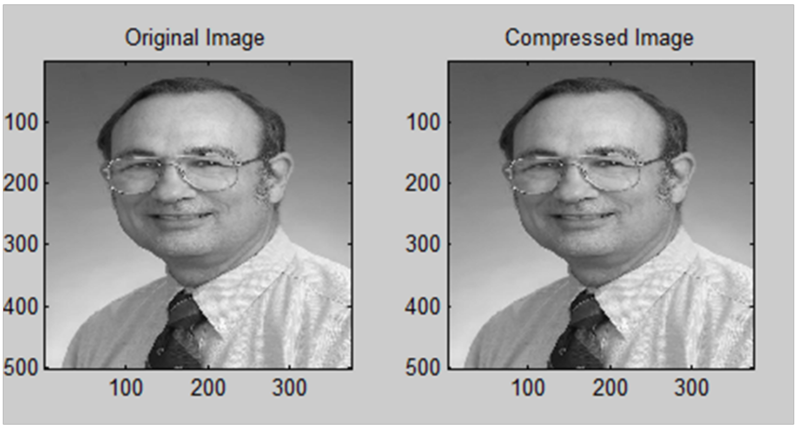

Figure 4.7: compressed image side by side with the original

PERF0 =49.8076 PERFL =99.9817 These returned values tell, respectively, what percentage of the wavelet coefficients Was set to zero and what percentage of the image's energy was preserved in the Compression process. Note that, even though the compressed image is constructed from only about half as many nonzero wavelet coefficients as the original, there is almost no detectable Deterioration in the image quality.

4.3 Multilevel de-noising

In this section we apply the experiments in the image by choosing number of noise level and different number of image de-noising resolution level from GUI interface as well as matlab code of de-noising and calculate and estimate the following parameter and Indicator like peak signal to noise ratio(PSNR) , the signal to noise ratio(SNR) and the mean squared error(MSE) .
To display the results of the levels of decomposition, type on the following menu and choose suitable one according to the noise

Choose amount of noise from list of noise in Figure4.8 and then add it to the gray scale image .

Apply Wavelet Transform Method to The Noisy Image shown in figure4.9 , then to decomposition the image in different level see the menu on figure4.10

Figure 4.8: Menu ‘wavelet Family’

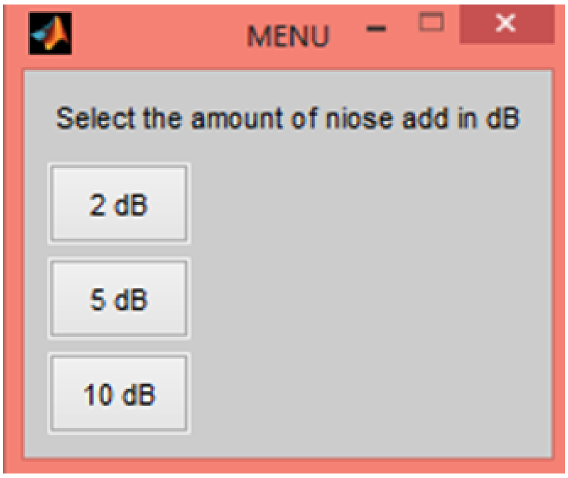

Figure 4.9: Menu ‘Noise Size’

Table (4.1) and table (4.2) represented the parameter of noisy image ,in table (4.1) the wavelet coefficient is 2 db it has been chosen from Figure4.8 the menu of wavelet family and the amount of noise added to the image is 5 db has been chosen from 4.9 and the number of decomposition level is 2 level of filtering that mean the noisy image will pass through low pass filter

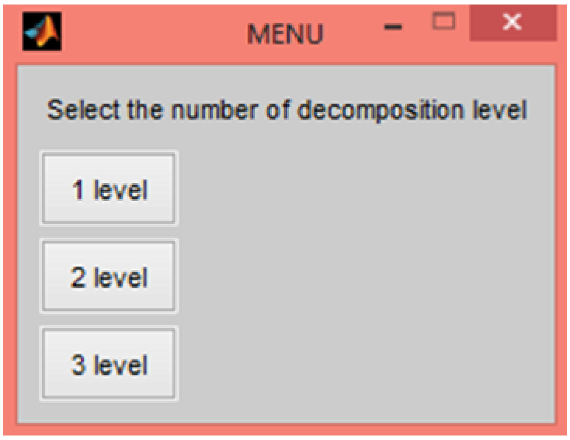

Figure 4.10: Menu 'Decomposition Level'

and high pass filter two times figure4.11 show the the filtering level of the noisy image . The given figures represent the approximation , horizontal ,

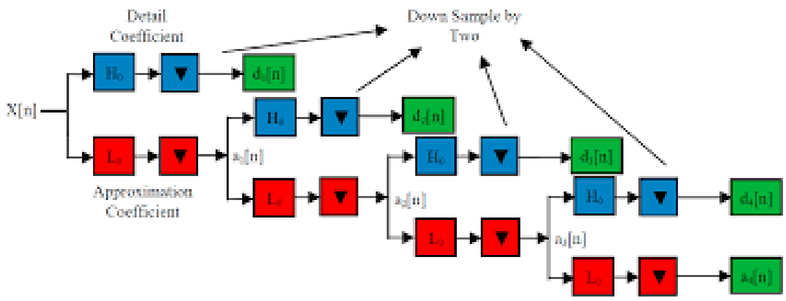

Figure 4.11: two level wavelet decomposition

vertical and diagonal details of the image after applying two level of decomposition Figure4.12 represent the output of de-noise image and also the table 4.3 show that the PSNR in the de-noise image is greater than PSNR in noisy image , SNR in de-noise image is greater than SNR in noisy image and MSE in de-noise image is less than MSE in noisy image. Peak Signal to Noise Ratio (PSNR) and Mean Square Error (MSE) are used to comparing the squared error between the original image and the reconstructed image.There is an inverse relationship between PSNR and MSE. So ahigher PSNR value indicates the higher quality of the image (better). The values for the PSNR in lossy image and video compression are between 30 and 50 dB, provided the bit depth is 8 bits, where higher is better. For 16-bit data typical values for the PSNR are between 60 and 80 dB.[5][6] Acceptable values for wireless transmission quality loss are considered to be about 20 dB to 25 dB

In this part of experiments the amount of noise has been increased and

Table 4.1: parameter of 2 level decomposition

Wavelet family	amount of noise	number of decomposition level
2 db	5 db	2

Table 4.2: parameter of 2 level noisy image before applying DWT

PSNR	SNR	MSE
19.606669	15.268698	0.010948

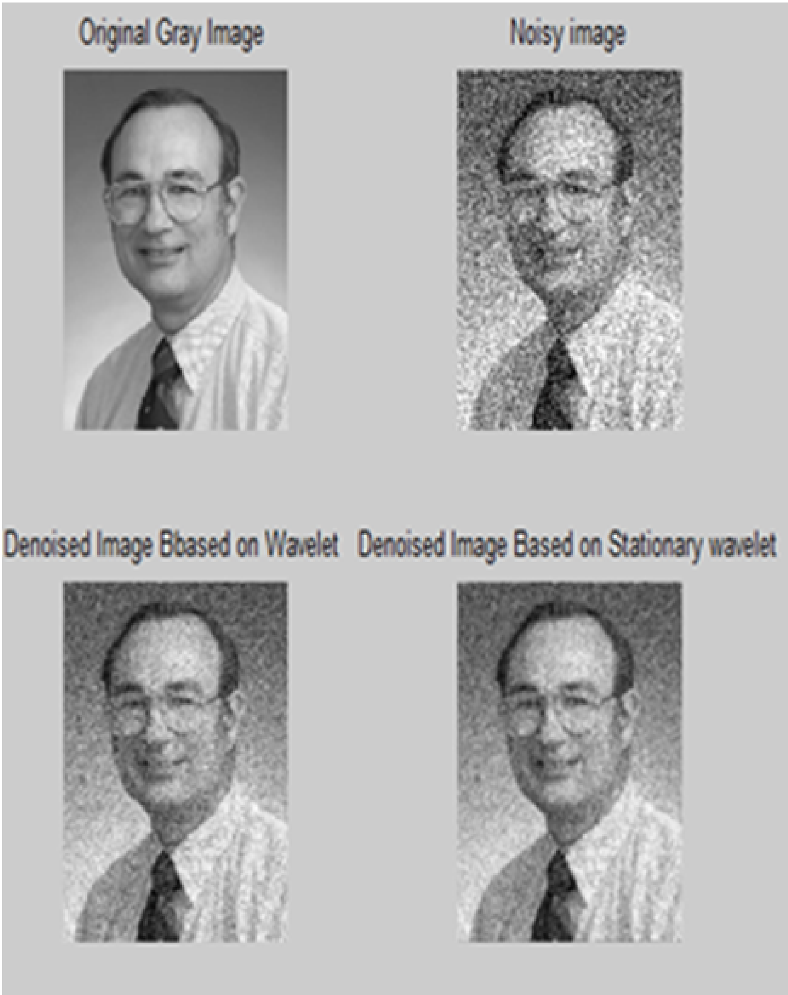

Figure 4.12: 'Result of 2 level Image decomposition'

amount of decomposition also increased from the menu of noise level and menu of decomposition level in Figure4.9 and Figure4.10 respectively to get more and more clear and de-noise image with high quality and resolution, it became 10 db of noise with number of decomposition is 3 level of filtering show in Figure4.13. those menu (wavelet family menu , noise level menu

Table 4.3: Result of 2 Level De-Noise Image

Parameter of de-noising Image	DWT	Stationary DWT
The peak signal to noise ratio of the reconstructed image	27.836547	28.993875
The signal to noise ratio of the reconstructed image	23.498576	24.655903
The mean squared error of the reconstructed image	0.001646	0.001261

Table 4.4: parameter of 3 level decomposition

Wavelet family	amount of noise	number of decomposition level
3 db	10 db	3

and decomposition menu)allow user to select suitable and perfect method to control the noisy image in different types of applications and give user high degree of purity on the noisy image . The result shown that the PSNR and SNR are increased from 24.501409 , 20.163438 in noisy image to 29.677112 and 25.339140 in the de-noise image and the MSE decreased from 0.003547 to 0.001077 , all result of 3 level of DWT shown in table (4.6)

4.4 Graphical User Interface (GUI) Results

This section takes you through the features of two-dimensional discrete wavelet analysis using the Wavelet Toolbox software. The toolbox provides these functions for image analysis. In this section we explore the same image as in the previous section, but we use the Graphical interface tools to analyze the image.

Table 4.5: parameter of 3 level noisy image before applying DWT

PSNR	SNR	MSE
24.501409	20.163438	0.003547

Table 4.6: Result of 3 Level De-Noising Image

Parameter of de-noising Image	DWT	Stationary DWT
The peak signal to noise ratio of the reconstructed image	29.677112	30.374443
The signal to noise ratio of the reconstructed image	25.339140	26.036472
The mean squared error of the reconstructed image	0.001077	0.000917

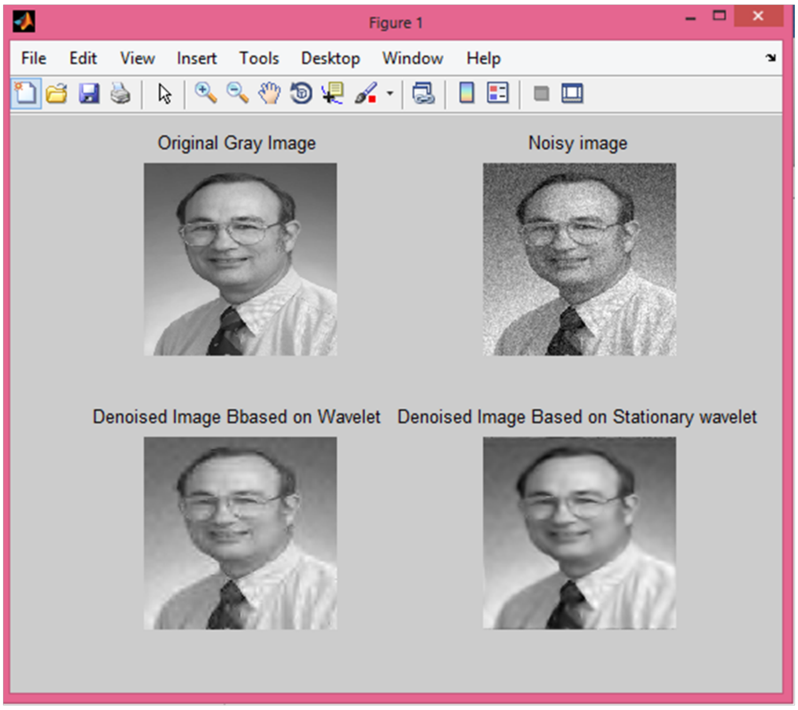

Figure 4.13: 'Result of 3 level Image de-noising'

4.4.1 Image De-noising (GUI)

Start the 2-D Wavelet Analysis Tool. From the MATLAB prompt, type wavemenu The Wavelet Tool Main Menu appears.show in figure 4.14

Click the Wavelet 2-Dmenu item. The discrete wavelet analysis tool for two dimensional Image data appears.

Load an image. From the File menu, choose the Load > Image option see figure4.15

When the Load Image dialog box appears, select the MAT-file wbarb.mat, which is in the MATLAB folder toolbox/wavelet/wavedemo. Click the OK button. The image is loaded into the Wavelet 2-D tool.

Figure 4.14: Wavelet Tool Main Menu

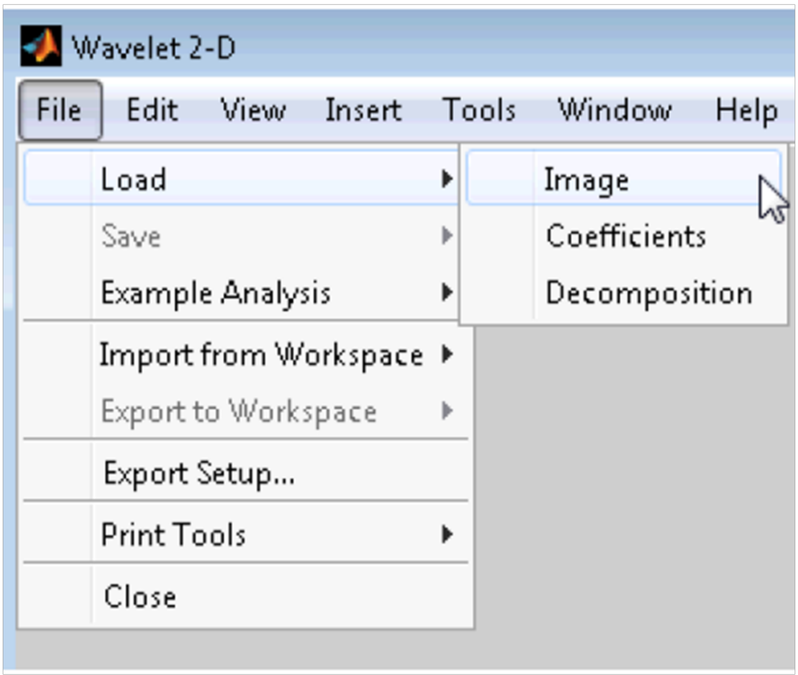

Figure 4.15: Load Image Option

Analyze the image. Using the Wavelet and Level menus located to the upper right, determine the Wavelet family, the wavelet type, and the number of levels to be used for the analysis. For this analysis, select the bior3.7 wavelet at level 2. Click the Analyze button. After a pause for computation, the Wavelet 2-D tool

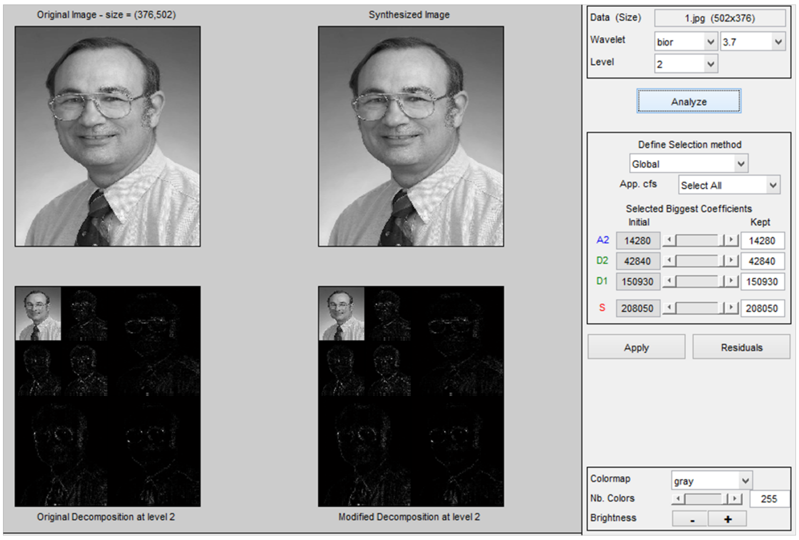

Figure 4.16: Apply DWT

4.4.2 Image CompressION Using (GUI)

Click the Compress button, located to the upper right of the Wavelet 2-Dwindow. The Wavelet 2-D Compression window appears. the following figure show that

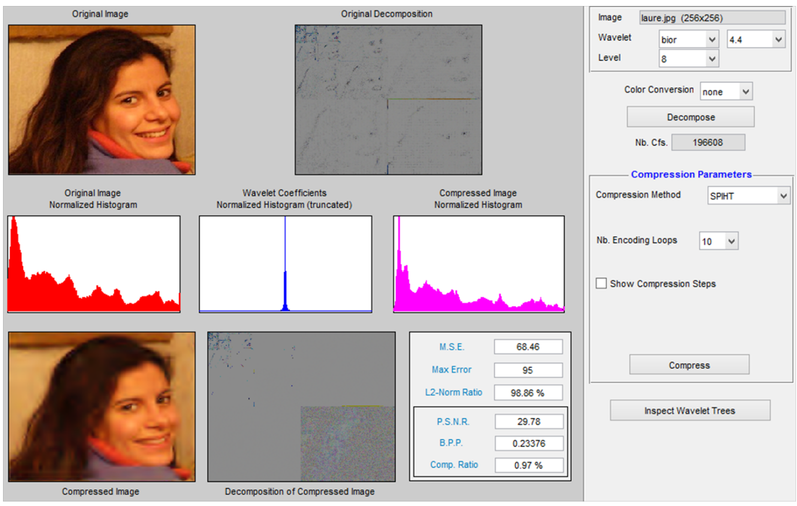

Figure 4.17: Image de-noising and Compression using DWT

4.4.2.1 Analysis of Compressed Image

The tool automatically selects thresholding levels to provide a good initial balance Between retaining the image's energy while minimizing the number of coefficients Needed to represent the image. However, you can also adjust thresholds manually using the By Level thresholding option, and then the sliders or edits corresponding to each level.

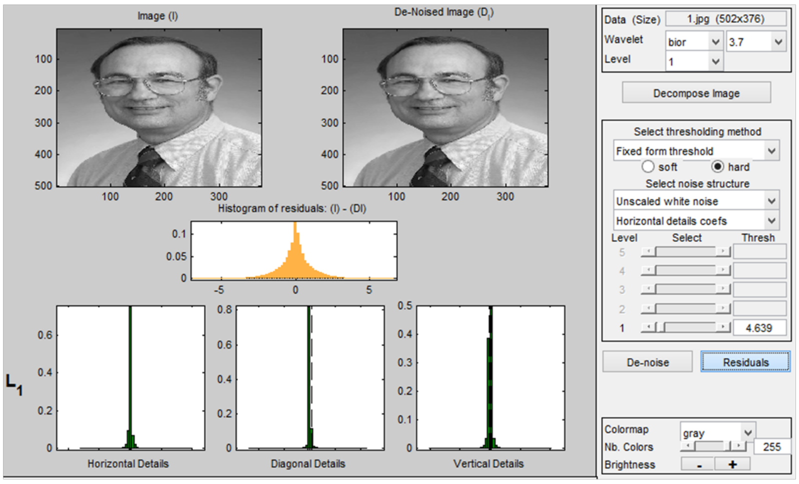

Figure 4.18: Image Thresholding

Select from the direction menu whether you want to adjust thresholds for horizontal, Diagonal or vertical details. To make the actual adjustments for each level, use the sliders or use the left mouse button to directly drag the yellow vertical lines. To compress the original image, click the Compress button. After a pause for computation, the compressed image is displayed beside the original. Notice that compression eliminates almost half the coefficients, yet no detectable deterioration of the image appears. .to Show the residuals. From the Wavelet 2-D Compression tool, click the Residuals button. The Moreon Residuals for Wavelet 2-D Compression window appears. Displayed statistics include measures of tendency (mean, mode, median) and dispersion (range, standard deviation). In addition, the tool provides frequency distribution diagrams (histograms and cumulative histograms). The same tool exists for the Wavelet 2-D De-noising tool. Note the statistics displayed in the above figure are related to the displayed image But not to the original one. Usually this information is the same, but in some cases, Edge effects may cause the original image to be cropped slightly. To see the exact statistics, use the command line functions to get the desired image and then apply The desired MATLAB statistical function(s). the following figure show that

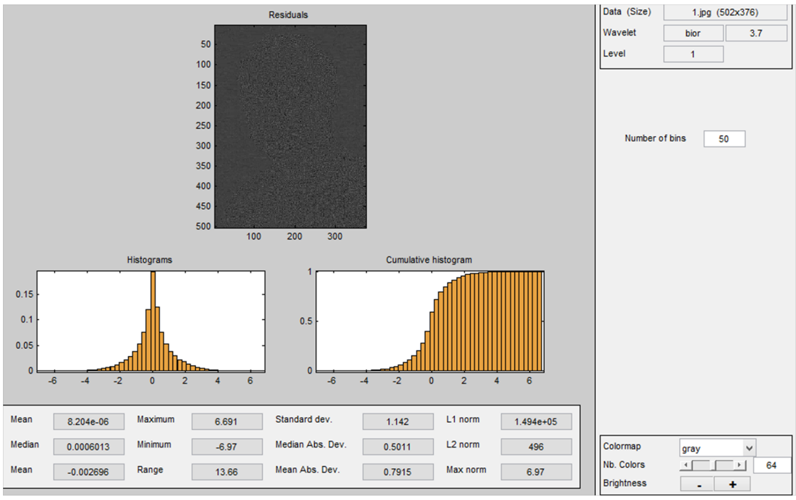

Figure 4.19: Image residuals

5 Chapter Five: Conclusion and Recommendations

5.1 Conclusion

In this thesis Image de-noising using wavelet transform has been discussed in the first part of the thesis. the sources of noise in the image and the algorithm used to remove it has been introduced in chapter two . In chapter three wavelet transform which is widely used in different scientific applications including signal and image processing has been explained . This ongoing growing success, which has been characterized by the adoption of some wavelet-based schemes, is due to features inherent to the transform, such as time-scale localization and multi-resolution capabilities The wavelet de-noising techniques offers high quality and flexibility for the noise problem of signals and image. We have taken the result by using matlab code , GUI with matlab code and GUI .The result show that using DWT increase the PSNR ,SNR in the image and decrease the MSE of de-noise image.Although compression in Wavelet . As a result we get the compressed image as well as noise free in vertical, horizontal and diagonal details and got energy ratio. JPEG 2000 is a much better image solution than the original JPEG file format. Using a sophisticated encoding method, JPEG 2000 files can compress files with less loss of, what we might consider, visual performance. In addition, the file format is less likely to be affected by 'bit errors' and other file system errors due to its more efficient coding structure.

5.2 Recommendations

There is always room for improvement. Multi-wavelets are relatively a new subject of study. Most current filters available have two, three or fourth order of approximation. Future construction methods may add even higher order of approximation, while preserving the desirable features of current methods. It most likely result in multi-filters that perform even better in image de-noising and compression applications. There is a possibility that in future many more multi-wavelet systems might be developed with matrix coefficients with higher order, which could provide even better results in the field of image de-noising and compression.

However, the current data compression methods might be far away from the ultimate limits. Interesting issues like obtaining accurate models of images, optimal representations of such models, and rapidly computing such optimal representations are the grand challenges facing the data compression community. Image coding based on models of human perception, scalability, robustness, error resilience, and complexity are a few of the many challenges in image coding to be fully resolved and may affect image data compression performance in the years to come. Although Future of image compression is progressive for 2D image and its goes on 3D image compression also. For 3D image compression as well as video compression used three dimensional mathematical Transforms with encoding techniques. In future image compression centered high compression ratio with quality improvement.

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Appendix A

1 Image De-noising Code

```
clear all;
close all;
clc

xx = imgetfile();
Io = imread(xx);

if(size(Io,3)==3)
     Id = rgb2gray(Io);
else
     Id = Io;
end

[M,N] = size(Id);

if log(M)/log(2) ≠ floor(log(M)/log(2))
     Dm = floor(log(M)/log(2));
     Mn = 2^Dm;
else
     Mn = M;
end
if log(N)/log(2) ≠ floor(log(N)/log(2))
     Dn = floor(log(N)/log(2));
     Nn = 2^Dn;
else
     Nn = N;
end
Id = imresize(Id,[Mn Nn]);

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

```

```
ww= menu('Select a wavelet family','db1', 'db2', 'db3', ...
    'sym3', 'coif2', 'bior2.2');
switch ww
     case 1
          wname = 'db1';
     case 2
          wname = 'db2';
     case 3
          wname = 'db3';
     case 4
          wname = 'sym3';
     case 5
          wname = 'coif2';
     case 6
          wname = 'bior2.2';
end

ss = menu('Select the amount of niose add in dB','2 dB', '5 ...
    dB', '10 dB');
switch ss
     case 1
          SNR = 2';
     case 2
          SNR = 5;
     case 3
          SNR = 10;
end

lev = menu('Select the number of decomposition level','1 ...
    level', '2 level', '3 level');

clear ww, clear ss, clear namefile, clear pathname;

figure(1)
subplot(2, 2, 1), imshow(Id), title('Original Gray Image')

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%// Adjust intensities in image I to range from 0 to 1
Im = double(Id)/255;

%// Add noise to image
randn('seed',212096);
```

```
v = var(Im(:)) / 10^(SNR/10);
I_noisy = imnoise(Im, 'gaussian', 0, v);

subplot(2, 2, 2), imshow(I_noisy), title('Noisy image')

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

Error1 = I_noisy - Im;                          % calculate ...
    the SNR by defination
SNR_1n = 10*log10(var(Im(:))/var(Error1(:)));      % ...
    calculate the SNR by defination

[PSNRn, SNRn] = psnr(I_noisy, Im);                 % ...
    calculate the SNR by Matlab function

mse_n = immse(Im, I_noisy);                     % calculate ...
    the mean square error by matlab function

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

[CA,CH,CV,CD] = dwt2(I_noisy,wname);

noiselev = median(abs(CD(:)))/0.6745;

thresh = sqrt(2*log(numel(I_noisy)))*noiselev;

clear CA, clear CH, clear CV, clear CD;
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

[c,l] = wavedec2(I_noisy,lev,wname);

Y = wthresh(c(prod(l(1,:))+1:end),'h',thresh);

c_n = c;
c_n(prod(l(1,:))+1:end) = Y;

Xr=waverec2(c_n,l,wname);

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

[PSNRr, SNRr] = psnr(Xr, Im);
mse_r = immse(Im, Xr);

```

```
Error2 = Xr − Im;                          % calculate the ...
    SNR by defination
SNR_r = 10*log10(var(Im(:))/var(Error2(:)));      % ...
    calculate the SNR by defination

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

subplot(2, 2, 3), imshow(Xr, []), title('Denoised Image ...
    Bbased on Wavelet')

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%
%%     Saionary wavele based denoising
%%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

[ca,chd,cvd,cdd] = swt2(I_noisy,lev,wname); % size of each ...
    marix depend on the number of levels

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

noiselev2 = median(abs(cdd(:)))/0.6745;

thresh2 = sqrt(2*log(numel(I_noisy)))*noiselev2;

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

Yhd = wthresh(chd,'h',thresh2);
Yvd = wthresh(cvd,'h',thresh2);
Ydd = wthresh(cdd,'h',thresh2);

Xr2 = iswt2(ca,Yhd,Yvd,Ydd,wname);
 subplot(2, 2, 4), imshow(Xr2, []), title('Denoised Image ...
     Based on Stationary wavelet')
clear ca, clear chd, clear cvd, clear cdd;
clear Yhd, clear Yvd, clear Ydd;
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
[PSNRrs, SNRrs] = psnr(Xr2, Im);
mse_rs = immse(Im, Xr2);
 % calculate the SNR by defination
Error2s = Xr2 − Im;
 % calculate the SNR by defination
SNR_rs = 10*log10(var(Im(:))/var(Error2s(:)));
```

```

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%
%% Result of Testing the algorithms
%%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

tx0 = sprintf('The wavelet family is %s\nThe number of ...
    decomposition level is %d\nwith %d dB SNR added to ...
    image\n',wname,lev,SNR);
disp(tx0)
tx1 = sprintf('The peak signal to noise ratio of the noisy ...
    image is          %f',PSNRn);
disp(tx1)
tx2 = sprintf('The signal to noise ratio of the noisy image ...
    is                %f',SNRn);
disp(tx2)
tx3 = sprintf('The mean squared error of the noisy image is ...
                      %f',mse_n);
disp(tx3)
tx10 = sprintf('\n Results of Denoising Algorithm Based on ...
    DWT \n');
disp(tx10)
tx4 = sprintf('The peak signal to noise ratio of the ...
    reconstructed image is %f',PSNRr);
disp(tx4)
tx5 = sprintf('The signal to noise ratio of the ...
    reconstructed image is      %f',SNRr);
disp(tx5)
tx6 = sprintf('The mean squared error of the reconstructed ...
    image is          %f',mse_r);
disp(tx6)

tx11 = sprintf('\n Results of Denoising Algorithm Based on ...
    Stationary DWT \n');
disp(tx11)
tx7 = sprintf('The peak signal to noise ratio of the ...
    reconstructed image is %f',PSNRrs);
disp(tx7)
tx8 = sprintf('The signal to noise ratio of the ...
    reconstructed image is      %f',SNRrs);
disp(tx8)
```

```
tx9 = sprintf('The mean squared error of the reconstructed ...
    image is          %f',mse_rs);
disp(tx9)

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
 clear tx0, clear tx1, clear tx2, clear tx3;
clear tx4, clear tx5, clear tx6, clear tx7;
clear tx8, clear tx9, clear tx10, clear tx11;
```

2 Image in Wavelet Transform Representation

```
clc;
clear all;
y=imread('1.jpg');
X=rgb2gray(y);
imshow(X)
%%To perform a single-level decomposition of the image ...
    using the bior3.7 wavelet,
%type

[cA1,cH1,cV1,cD1] = dwt2(X,'bior3.7');
%%%%%%To construct the level-one approximation and details ...
    (A1, H1, V1, and D1) from the
%%coefficients cA1, cH1, cV1, and cD1
A1 = upcoef2('a',cA1,'bior3.7',1);
H1 = upcoef2('h',cH1,'bior3.7',1);
V1 = upcoef2('v',cV1,'bior3.7',1);
D1 = upcoef2('d',cD1,'bior3.7',1);
%%%%%%%%%%%To display the results of the level 1 ...
    decomposition, type
%colormap(map);
subplot(2,2,1); image(wcodemat(A1,192));
title('Approximation A1')
subplot(2,2,2); image(wcodemat(H1,192));
title('Horizontal Detail H1')
subplot(2,2,3); image(wcodemat(V1,192));
title('Vertical Detail V1')
subplot(2,2,4); image(wcodemat(D1,192));
title('Diagonal Detail D1')

```

```
%%%6 Regenerate an image by single-level Inverse Wavelet ...
    Transform.
%To find the inverse transform, type
Xsyn = idwt2(cA1,cH1,cV1,cD1,'bior3.7');
%%%To perform a level 2 decomposition of the image (again ...
    using the bior3.7 wavelet),
%type
[C,S] = wavedec2(X,2,'bior3.7');
%To extract the level 2 approximation coefficients from C, type
cA2 = appcoef2(C,S,'bior3.7',2);
```

3 Image Compression

```
%WAVELET BASED COMPRESSION
 %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

 %removes all variables, globals, functions and
%MEX links(MATLAB loads and runs a different entry point ...
    symbol for C or Fortran MEX-files)
clear all;
% CLOSE ALL  closes all the open figure windows.
close all;
%read the image
input_image1=imread('cameraman.tif');
%display input image
%add noise
input_image=imnoise(input_image1,'speckle',.01);
figure;
imshow(input_image);
%give the number of decomposition level which must be ...
    integer and should not exceed 3
% n=input('enter the decomposition level');
n=4;
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
[Lo_D,Hi_D,Lo_R,Hi_R] = wfilters('dB2');
% computes four filters associated with the orthogonal or ...
    biorthogonal
%  wavelet named in the string 'wname'.
%    The four output filters are:
 %       LO_D, the decomposition low-pass filter
```

```
%        HI_D, the decomposition high−pass filter
 %       LO_R, the reconstruction low−pass filter
  %      HI_R, the reconstruction high−pass filter
  % Available wavelet names 'wname' are:
  % Daubechies: 'db1' or 'haar', 'db2', ... ,'db45'
   %Coiflets  : 'coif1', ... ,  'coif5'
   %Symlets   : 'sym2' , ... ,  'sym8', ... ,'sym45'
   %Discrete Meyer wavelet: 'dmey'
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%wavedec2    − Multi−level 2−D wavelet decomposition.
 [c,s]=wavedec2(input_image,n,Lo_D,Hi_D);

% gives the wavelet decomposition of the matrix input_image ...
    at level n, using the
% wavelet named in string 'wname' or low pass and high pass
% Outputs are the decomposition vector C and the
%corresponding bookkeeping matrix S.
disp(' the decomposition vector Output is');
disp(c);
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%Thresholds for wavelet 2−D using Birge−Massart strategy.
 [thr,nkeep] = wdcbm2(c,s,1.5,3*prod(s(1,:)));

 % give level−dependent thresholds 'thr'and numbers of ...
     coefficients to be kept 'nkeep'
 % for compression. 'thr' is obtained using a wavelet ...
     coefficients
 %selection rule based on Birge−Massart strategy.
  %disp('level−dependent thresholds');
 %disp(thr);
 %disp(' numbers of coefficients to be');
 %disp(nkeep);
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
  %compression using wavelet packets.
  [compressed_image,TREED,comp_ratio,PERFL2] ...
     =wpdencmp(thr,'s',n,'dB2','threshold',5,1);
  disp('compression ratio in percentage');
  disp(comp_ratio)
 % returns a compressed version compressed_image of input
 % signal 'thr' (2−D) obtained by wavelet packet  ...
     coefficients thresholding.
```

```
 % The additional output argument TREED is thed
 % wavelet packet best tree decomposition of ...
    compressed_image.
 % PERFL2 and PERF0 are L^2 recovery and compression ...
    scores in percentages.

 %Multi-level 2-D wavelet reconstruction.
re_ima1 = waverec2(c,s,'dB2');
re_ima=uint8(re_ima1);
 subplot(1,3,1);
imshow(input_image);
 title('i/p image');
subplot(1,3,2);
imshow(compressed_image);
 title('compressed image');
subplot(1,3,3);
imshow(re_ima);
 title('reconstructed image');
```

4 RGB Images Compression

```
% Wavelet image compression - RGB images
clear all;
close all;
% % Reading an image file
% im = input('Enter a image');
X=imread('cameraman.tif');
% inputting the decomposition level and name of the wavelet
% n=input('Enter the decomposition level');
n=4;
% wname = input('haar');
 x = double(X);
NbColors = 255;
map = gray(NbColors);
 x = uint8(x);
%Conversion of RGB to Grayscale
% x = double(X);
% xrgb  = 0.2990*x(:,:,1) + 0.5870*x(:,:,2) + 0.1140*x(:,:,3);
% colors = 255;
% x = wcodemat(xrgb,colors);
```

```
% map = pink(colors);
% x = uint8(x);
% A wavelet decomposition of the image
[c,s] = wavedec2(x,n,'dB2');
% wdcbm2 for selecting level dependent thresholds
alpha = 1.5; m = 2.7*prod(s(1,:));
[thr,nkeep] = wdcbm2(c,s,alpha,m)
% Compression
[xd,cxd,sxd,perf0,perfl2] = wdencmp('lvd',c,s,'dB2',n,thr,'h');
disp('Compression Ratio');
disp(perf0);
% Decompression
R = waverec2(c,s,'dB2');
 rc = uint8(R);
% Plot original and compressed images.
subplot(221), image(x);
colormap(map);
title('Original image')
subplot(222), image(xd);
colormap(map);
title('Compressed image')
% Displaying the results
xlab1 = ['2-norm rec.: ',num2str(perfl2)];
xlab2 = [' % -- zero cfs: ',num2str(perf0), ' %'];
xlabel([xlab1 xlab2]);
subplot(223), image(rc);
colormap(map);
title('Reconstructed image');
%Computing the image size
disp('Original Image');
imwrite(x,'original.tif');
imfinfo('original.tif')
disp('Compressed Image');
imwrite(xd,'compressed.tif');
imfinfo('compressed.tif')
disp('Decompressed Image');
imwrite(rc,'decompressed.tif');
imfinfo('decompressed.tif')
```