“Wavelet based performance analysis of image compression in different methods”

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APPROVAL

This project titled **"wavelet based Performance analysis of image compression in different method"** submitted By **A.S.M Shaem** to the Department of Electronics and Telecommunication Engineering, Daffodil International University, Dhaka has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Electronics and Telecommunication Engineering and approved as to its style and contents. The presentation has been held 27th August 2012.

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DECLARATION

I hereby declare that, this project has been done by me under the supervision of **Md. Taslim Arefin,** Assistant Professor, Department Of Electronics and Telecommunication Engineering, Daffodil International University, Dhaka. I also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

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ABASTRACT

In this thesis, my aim is to compare for the different wavelet-based image compression techniques. The effects of different wavelet functions filter orders, number of decompositions, image contents and compression ratios were examined. The results of the above techniques WDR, ASWDR, STW, SPIHT, EZW etc., were compared by using the parameters such as PSNR, MSE BPP values from the reconstructed image. These techniques are successfully tested by four different images.

TABLE OF CONTENT

	Page
Approval	i
Declaration	ii
Acknowledgments	iii
Abstract	iv
Table of contents	vii-viii
List of Figures	ix
List of Tables	x

CHAPTER 1
Introduction

1.	General Introduction	1
1.1	Principles behind Compression	1
1.2	Aim of the Research Work	2
1.3	Organization of Thesis	2
1.4	Contribution of Thesis	3
1.5	Focus of the Thesis	3

CHAPTER 2
Theory Background

2.1	Aims and objective	4
2.2	Overview	4
2.3	Image Compression	5
2.4	Lossy Compression	5
2.5	Wavelet	7
2.6	What is Wavelet Analysis?	7
2.7	Wavelet VS. Fourier Transforms	9
2.7.1	Similarities between Fourier & Wavelet Transform	9
2.7.2	Dissimilarities between Fourier & Wavelet Transform	9
2.8	What is Wavelet Tool?	10
2.8.1	Command line Function	10
2.8.2	Graphical Interactive tools	11
2.9	Wavelet Families	11
2.9.1	Haar	13
2.9.2	Daubechies	13
2.9.3	Biorthogonal	13
2.10	Advantage of Wavelet	13
2.11	Applications	14

CHAPTER 3

Analysis of Image Compression Method

(Wavelet Based True Compression)

3.1 Introduction 15
3.2 Working Principle 17

CHAPTER 4
Overall Performance Analysis

Introduction 20
4.1 Embedded Zero Wavelet (EZW) 20
4.2 Set Partitioning in Hierarchical Trees (SPIHT) 23
4.3 Wavelet Difference Reduction (WDR) 25
4.4 Adaptively Scanned Wavelet Difference Reduction (ASWDR) 27
4.5 Spatial-orientation Tree Wavelet (STW) 29

CHAPTER 5
Simulation and Result

5.1 MATLAB Simulation 35
5.2 Discussion 38

CHAPTER 6
Conclusion & Future Scope

40
References 41-42
Appendix

List of Figure

Fig. 1. Compression Technique of an image	6
Fig.2.2 Sin Wave and Wavelet	8
Fig.2.3 Screenshot of Wavelet manus	11
Fig 3.1 Different image which will compress	16
Fig 3.2: Block Diagram of Procedure	17
Fig. 3.3 Screenshot of Wavelet manus	18
Fig. 3.4 MATLAB 2-D image compression interface	19
Fig. 4.1 Compress screenshot of four image using in EZW method	22
Fig. 4.2 Compress screenshot of four image using in SPIHT method	24
Fig. 4.3 Compress screenshot of four image using in WDR method	26
Fig. 4.4 Compress screenshot of four image using in ASWDR method	28
Fig. 4.5 Compress screenshot of four image using in STW method	30
Fig. 5.1 Graph-1 (For Total Analytical Result)	32
Fig. 5.2 Graph-2 (For BPP vs. MSE)	33
Fig. 5.3 Graph-3 (For BPP vs. PSNR)	33
Fig. 5.4 Graph-4 (Overall Performance of CR, PSNR, BPP, MSE)	34
Fig. 5.5 Bit Per Pixel vs. Mean Square error	35
Fig. 5.6 Bit Per Pixel vs. Peak Signal to Noise Ratio	35
Fig. 5.7 Graphical Representation of BPP vs. MSE for all Methods	36
Fig. 5.8 Graphical Representation of BPP vs. PSNR for all Methods	37

List of Table

Tabel-1: Compression Ratio of Bit Per Pixel and PSNR Result for (512*512*3) (EZW Method) 21

Table-2: Compression Ratio of Bit Per Pixel and PSNR Result for (512*512*3) (SPIHT Method) 23

Table-3: Compression Ratio of Bit Per Pixel and PSNR Result for (512*512*3) (WDR Method) 26

Table-4: Compression Ratio of Bit Per Pixel and PSNR Result for (512*512*3) (ASWDR Method) 27

Table-5: Compression Ratio of Bit Per Pixel and PSNR Result for (512*512*3) (STW Method) 29

Table-6: Total analytical Result for (512*512*3) image 31

Table-7: Average Result for 4 (512*512*3) image 33

Chapter 1

Introduction

1. General Introduction:

Present day large amounts of images are stored, processed and transmitted and hence there is a great need for the compression of an image to save memory, transmission bandwidth etc. For many applications, simply reducing the file size or simple compression is not sufficient some additional scalable and embedded properties are also required. Discrete Wavelet Transform (DWT) provides a multi resolution image representation and has become one of the most important tools in image analysis and coding over the last two decades.[1] Wavelet transforms have been widely studied over the last decade. At the present state technology, the only solution is to compress multimedia data before its storage and transmission, and decompress it at the receiver for playback. For example for a compression Ratio of 32:1 ,the space, bandwidth and the transmission time requirements can be reduced by a factor of 32,with acceptable quality. The fundamental goal of image compression is to reduce the bit rate for transmission or storage while maintaining an acceptable fidelity or image. One of the most successful applications of wavelet methods is transform-based image compression (also called coding).Wavelet-based coding provides substantial improvements in picture quality at higher compression ratios.

1.1 Principles behind Compression

A Common characteristic of most images is that the neighboring pixels are correlated and therefore contain redundant information. The foremost task then is to find less correlated representation of the Image. Twofundamental components of compression are redundancy and irrelevancy reduction. Redundancy reduction aims at removing duplication from the signal source (image/video).Irrelevancy reduction omits parts of the signal that will not be noticed by the signal receiver namely Human Visual System (HVS).In general three types of redundancy can be identified:

- ✓ Spatial Redundancy or correlation between neighboring pixels.
- ✓ Spectral redundancy or correlation between different color planes or spectral band
- ✓ Temporal redundancy or correlation between adjacent frames in a sequence of images (in video applications).

Image compression research aims at reducing the number of bits needed to represent an image by removing the spatial and spectral redundancies as much as possible.

1.2 Aim of the Research Work:

This thesis Paper Presents the Analysis of different wavelet based image compression Techniques. The existing Techniques, WDR, ASWDR, STW, SPHIT, EZW have been introduce and evaluated based on the parameters like PSNR, MSE, BPP. Acceptable image quality has been extracted in terms of the performance parameter and coding technique. The result is extracted from the experiment empirically and shows that the EZW and STW technique performs better than WDR and other method in terms of the parameters. The analysis has been tested and verified Using MATLAB.

1.3 Organization of thesis

This thesis provides an overview of Image compressions using the Wavelet transform with the help of the MATLAB software. This section is intended to give a short overview of the thesis, by describing the outline of each chapter.

- ➢ **Chapter 2.**Theory Background
- ➢ **Chapter 3.**Analysis Of Image Compression Method
- ➢ **Chapter 4**. Overall Performance Analysis
- ➢ **Chapter 5.**Simulation And Result
- ➢ **Chapter 6** Conclusion And Future Scope

1.4 Contribution of thesis

The ultimate objective of this thesis is to compare the best performance analysis of image compression method in different situation as like compression ratio, bit per pixel, peak signal to noise ratio, level, compression parameters, color map, mean square error, normalized ratio, etc. and I individually checked the compression technique and collecting real life data for individual method, which allows the compare of different measurement.

1.5 Focus of the Thesis

This thesis studies Wavelet based Performance analysis of image compression in different method, and I focus on, when BPP is less & CR is good as well then the PSNR is high after compressing the original images. I apply this theme in different method & checked performance where it is provide its best result.

Chapter 2
Theory Background

2.1 Aims and objectives

Everywhere around us are signals that can be analyzed. For example, there are seismic tremors, human speech, engine vibrations, financial data, medical images, music and many other types of signals. Wavelet analysis is a new and promising set of tools and techniques for analyzing these signals.

2.2 Overview

The fundamental idea behind wavelets is to analyze according to scale. Indeed, some researchers in the wavelet field feel that, by using wavelets, one is adopting a whole new mindset or perspective in processing data.

Wavelets are functions that satisfy certain mathematical requirements and are used in representing data or other functions. This idea is not new. Approximation using superposition of functions has existed since the early 1800's, when Joseph Fourier discovered that he could superpose sine and cosines to represent other functions. However, in wavelet analysis, the scale that we use to look at data plays a special role. Wavelet algorithms process data at different scales or resolutions. If we look at a signal with a large window, we would notice gross features. Similarly, if we look at a signal with a small window, we would notice small features. The result in wavelet analysis is to see both the forest and the trees, so to speak.

This makes wavelets interesting and useful. Wavelets are well-suited for approximating data with sharp discontinuities. The wavelet analysis procedure is to adopt a wavelet prototype function, called an analyzing wavelet or mother wavelet. Temporal analysis is performed with a contracted, high-frequency version of the prototype wavelet, while frequency analysis is performed with a dilated, low frequency version of the same wavelet. Because the original signal or function can be represented in terms of a wavelet expansion, data operations can be performed using just the corresponding wavelet coefficients.

Other applied fields that are making use of wavelets include astronomy, acoustics, nuclear engineering, sub-band coding, signal & image processing, neurophysiology, music, magnetic resonance imaging, speech discrimination, optics, fractals, turbulence, earthquake prediction, radar, human vision, and pure mathematics applications such as solving partial differential equations.

2.3 Image compression

There are two types of image compression: lossless and lossy. With lossless compression, the original image is recovered exactly after decompression. Unfortunately, with images of natural scenes it is rarely possible to obtain error free compression at a rate beyond 2:1. Much higher compression ratios can be obtained if some error, which is usually difficult to perceive, is allowed between the decompressed image and the original image. This is lossy compression. In many cases, it is not necessary or even desirable that there be error-free reproduction of the original image. For example, if some noise is present, then the error due to that noise will usually be significantly reduced via some de-noising method. In such a case, the small amount of error introduced by lossy compression may be acceptable. Another application where lossy compression is acceptable is in fast transmission of still images over the Internet. We shall concentrate on wavelet-based lossy compression of grey-level still images. When there are 256 levels of possible intensity for each pixel, then we shall call these images 8 bpp (bits per pixel) images. Images with 4096 grey- levels are referred to as 12 bpp. Some brief comments on color images will also be given, and we shall also briefly describe some wavelet-based lossless compression methods.

2.4Lossy compression

The methods of lossy compression that we shall concentrate on are the following: the EZW algorithm, the SPIHT algorithm, the WDR algorithm, and the ASWDR algorithm. These are relatively recent algorithms which achieve some of the lowest errors per compression rate and highest perceptual quality yet reported. After describing these algorithms in detail, we shall list some of the other algorithms that are available. The five stages of compression are shown in Figs. All of the steps shown in the compression diagram are invertible, hence lossless, except for the Quantize step. Quantizing refers to a reduction of the precision of the floating point values of the wavelet transform, which are typically either 32- bit or 64-bit floating point numbers. To use less bits in the compressed transform—which is necessary if compression of 8 bit per pixel or 12bit per pixel images is to be achieved—these transform values must be expressed with less bits for each value. This leads to rounding error. These approximate, quantized, wavelet transforms will produce approximations to the images when an inverse transform is performed. Thus creating the error inherent in lossy compression.

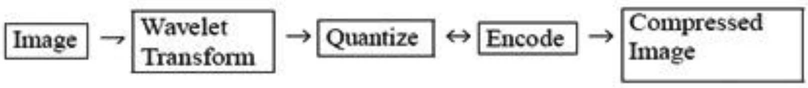

Figure: Compression technique of an image

The relationship between the Quantize and the Encode steps, shown in Fig. 1, is the crucial aspect of wavelet transform compression. Each of the algorithms described below takes a different approach to this relationship. The purpose served by the Wavelet Transform is that it produces a large number of values having zeroed, or near zero, magnitudes. Two commonly used measures for quantifying the error between images are Mean Square Error (MSE) and Peak Signal to Noise Ratio (PSNR). The MSE between two images A and B is defined by

$$\mathrm{MSE} = \frac{1}{N} \sum_{j,k} (f[j,k] - g[j,k])^2$$

Where the sum over C, D denotes the sum over all pixels in the images and N is the number of pixels in each image.

$$PSNR = 10\log_{10} \frac{255^2}{MSE} .$$

PSNR tends to be cited more often, since it is a logarithmic measure, and our brains seem to respond logarithmically to intensity. Increasing PSNR represents increasing fidelity of compression.

A lower value for MSE means lesser error, and as seen from the inverse relation between the MSE and PSNR, this translates to a high value of PSNR. Logically, a higher value of PSNR is good because it means that the ratio of Signal to Noise is higher. Here, the 'signal' is the original image, and the 'noise' is the error in reconstruction. So, a compression scheme having a lower MSE (and a high PSNR), can be recognized as a better one.

2.5 Wavelet

A wavelet is a wave-like oscillation with amplitude that starts out at zero, increases, and then decreases back to zero. It can typically be visualized as a "brief oscillation" like one might see recorded by a seismograph or heart monitor. Generally, wavelets are purposefully crafted to have specific properties that make them useful for signal processing. Wavelets can be combined, using a "reverse, shift, multiply and sum" technique called convolution, with portions of an unknown signal to extract information from the unknown signal.

2.6 What is wavelet analysis?

Wavelet analysis represents the next logical step: a windowing technique with variable-sized regions. Wavelet analysis allows the use of long time intervals where we want more precise low frequency information, and shorter regions where we want high-frequency information.

Now that we know some situations when wavelet analysis is useful, it is worthwhile asking “What is wavelet analysis?” and even more fundamentally, “What is a wavelet?”

A wavelet is a waveform of effectively limited duration that has an average value of zero.

Comparing wavelets with sine waves; which are the basis of Fourier analysis, it is found that sinusoids do not have limited duration, they extend from minus to plus infinity. And where sinusoids are smooth and predictable, wavelets tend to be irregular and asymmetric.

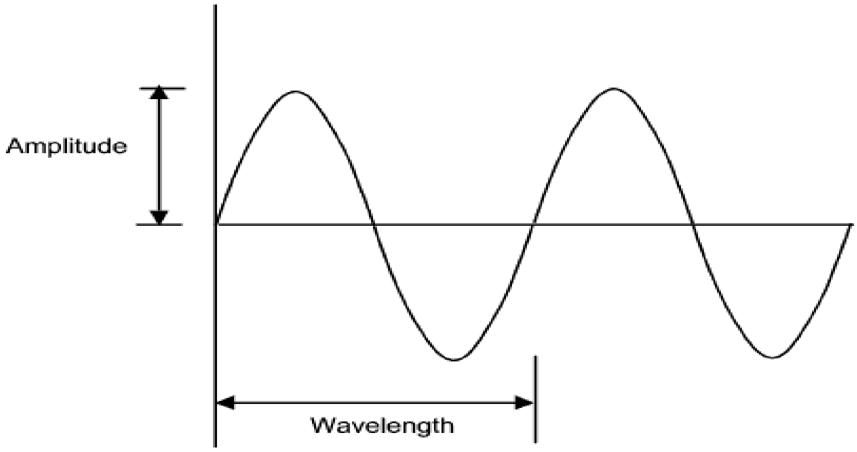

Figure: Sine wave

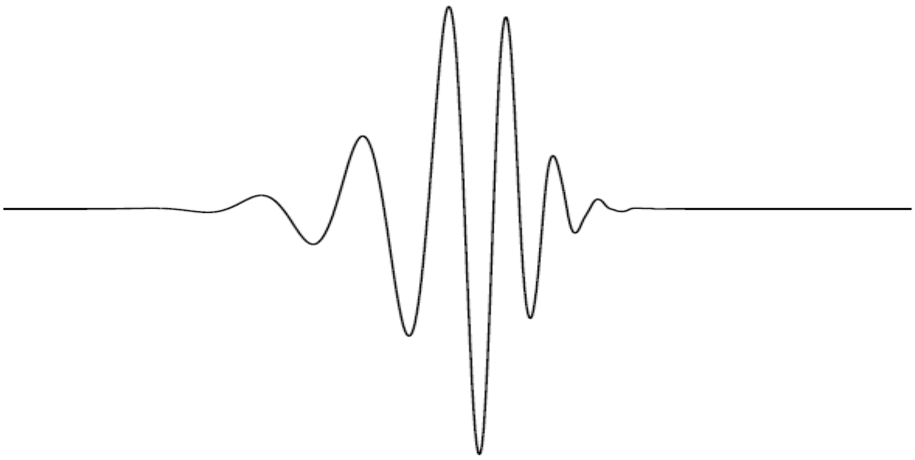

Figure: Wavelet (db10)

Figure: 2-2Sine wave and Wavelet (db10)

Fourier analysis consists of breaking up a signal into sine waves of various frequencies; similarly, wavelet analysis is the breaking up of a signal into shifted and scaled versions of the original (or mother) wavelet.

Just looking at pictures of sine waves and wavelets, we can see intuitively that signals with sharp changes might be better analyzed with an irregular wavelet than a smooth sinusoid, just as some foods are better handled with a fork than a spoon.

It also makes sense that local features can be described better with wavelets that have local extent.

2.7 Wavelet VS. Fourier transforms

2.7.1 Similarities between Fourier & Wavelet transform

The fast Fourier transforms (FFT) and the discrete wavelet transform (DWT) are both linear operations that generate a data structure that contains $\log_2 n$ segments of various lengths, usually filling and transforming it into a different data vector of length 2^n.

The mathematical properties of the matrices involved in the transforms are similar as well. The inverse transform matrix for both the FFT and DWT is the transpose of the original. As a result, both transforms can be viewed as a rotation in function space to a different domain. For the FFT, this new domain contains basis functions that are sine and cosine. For the wavelet transform, this new domain contains more complicated basis functions called wavelets, mother wavelets or analyzing wavelets.

Both transforms have another similarity. The basic functions are localized in frequency, making mathematical tools such as power spectra and scalegrams useful at picking out frequencies and calculating power distributions.

2.7.2 Dissimilarities between Fourier & Wavelet transform

The most interesting dissimilarity between two kinds of transforms is that individual wavelet functions are localized in space. Fourier sine and cosine functions are not. This localization feature, along with wavelets' localization of frequency, makes many functions and operators using wavelets "sparse" when transformed into the wavelet domain. This sparseness, in turn, results in a number of useful applications such as image& data compression, detecting features in images, & removing noise from time series.

An advantage of wavelet transforms is that the windows vary. In order to isolate signal discontinuities, one would like to have some very short basis functions.

2.8 What is Wavelet tool?

The wavelet toolbox is a collection of functions built on the MATLAB technical computing environment. It provides tools for the analysis and synthesis of signals, images, and tools for statistical applications, using wavelet and wavelet packets within the framework of MATLAB.

The Math Works provides several products that are relevant to the kinds of tasks that can be performed with the Wavelet toolbox.

The wavelets toolbox provides two categories of tools:

- Command line function and
- Graphical interactive tools

2.8.1 Command line function

The first category of tools is made up of functions that can be call directly from the command line or from own applications. Most of these functions are M-files, series of statements that implement specialized wavelet analysis or synthesis algorithms. The code can be viewable for these functions using the following statements:

function_name

The header can be viewed of the function, help part, using the statement:

helpfunction_name

A summary list of the wavelet toolbox functions is available by typing

help wavelet

The way can be changed of any toolbox function works by copying and renaming the M-file, then modifying the copy. These tools can also be extended by adding own M-files.

2.8.2 Graphical interactive tools

The second category of tools is a collection of graphical interface tools that afford access to extensive functionality. These tools can be accessed by typing from the command line.

wavemenu

2.9 Wavelet families

Several families of wavelets that have proven to be especially useful are included in this toolbox. What follows is an introduction to some wavelet families.

a) Type *wavemenu* from the MATLAB command line. The wavelet toolbox main menu appears.
b) Click the Wavelet Display menu item, the Wavelet Display tools appears.
c) Select a family from the Wavelet menu at the top right of the tool.
d) Click the Display button .Pictures of the wavelets and their associated filters appears.
e) Obtain more information by clicking the information buttons located at the right.

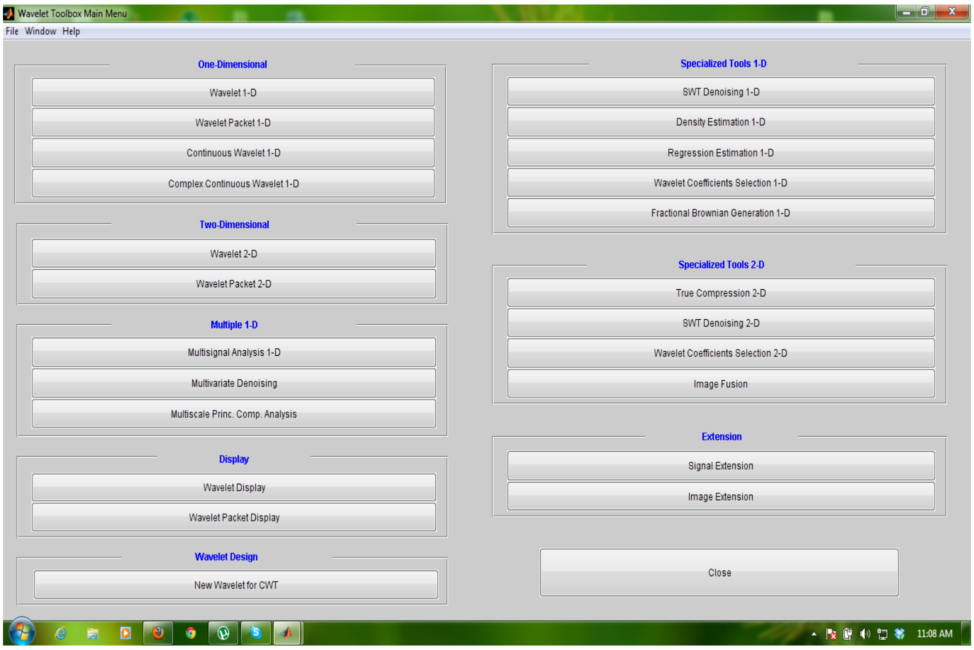

Figure: 2-3 Screenshot of Wavelet menus.

Family short name	Wavelet family name
‘haar’	Haar wavelet
‘db’	Daubechies wavelets
‘sym’	Symlets
‘coif’	Coiflets
‘bior’	Biorthogonal wavelets
‘rbio’	Reverse Biorthogonal wavelets
‘meyr’	Meyer wavelets
‘dmey’	Discrete approximation of Meyer wavelets
‘gaus’	Gaussian wavelets
‘mexh’	Mexican hat wavelets
‘morl’	Morlet wavelet
‘cgau’	Complex Gaussian wavelets
‘shan’	Shannon wavelets
‘fbsp’	Frequency B-spline wavelets
‘cmor’	Complex Morlet wavelets

Figure: Wavelet Families

2.9.1 Haar

Any discussion of wavelets begins with 'Haar' wavelet, the first and simplest. Haar wavelet is discontinuous, and resembles a step function. It represents the same wavelet as Daubechies db1.

2.9.2 Daubechies

Ingrid Daubechies, one of the brightest stars in the world of wavelet research, invented what are called compactly supported orthogonal wavelets, thus making discrete wavelet analysis practicable, The names of the Daubechies family wavelets are written dbN, where N is the order, and db the "surname" of the wavelet. The db1 wavelet, as mentioned above, is the same as Haar wavelet.

2.9.3 Biorthogonal

This family of wavelets exhibits the property of linear phase, which is needed for signal and image reconstruction. By using two wavelets, one for decomposition and other for reconstruction instead of the same single one, interesting properties are derived.

2.10 Advantage of Wavelet:

Many applications use the wavelet decomposition taken as a whole. The common goals concern the signal or image clearance and simplification, which are part of de-noising or compression. I find many published papers in oceanography and earth studies. One of the most popular successes of wavelets is the compression of FBI fingerprints.

When trying to classify the applications by domain, it is almost impossible to sum up several thousand papers written within the last 15 years. Moreover, it is difficult to get information on real-world industrial application from companies. They understandably protect their own information.

Some domains are very productive. Medicine is one of them. We can find studies on micro-potential extraction in EKGs, on time localization of His bundle electrical heart activity, in ECG noise removal. In ECGs, a quick transitory signal is drowned in the usual one. The wavelets are able to determine if a quick signal exists, and if so, can localized it. There are attempts to enhance mammograms to discriminate tumors from calcifications.

Another prototypical application is a classification of Magnetic Resonance Spectra. The study concerns the influence of the fat we eat on our body fat. The type of feeding is the basic information and the study is intended to avoid taking a sample of the body fat. Each Fourier spectrum is encoded by some of its wavelet coefficients. A few of them are enough to code the most interesting features of the spectrum. The classification is performed on the coded vectors.

2.11 Applications

There are few applications of wavelet in different sectors:

- Discontinuities and breakdown points I
- Detecting Discontinuities and Breaking points II
- Detecting Long-Term Evolution
- Detecting Self-Similarity
- Identifying Pure Frequencies
- Suppressing Signals
- De-Noising Signals
- De-Noising Images
- Compressing Images and
- Fast Multiplication of Large Matrices.

Chapter 3

Analysis of Image Compression method

(Wavelet Based True Compression)

3.1 Introduction

As a mathematical tool, wavelets can be used to extract information from many different kinds of data, including – but certainly not limited to – audio signals and images. Sets of wavelets are generally needed to analyze data fully. A set of "complementary" wavelets will deconstruct data without gaps or overlap so that the deconstruction process is mathematically reversible. Thus, sets of complementary wavelets are useful in wavelet based compression/decompression algorithms where it is desirable to recover the original information with minimal loss. There are many compression methods in wavelet section like:

- **EZW (Embedded Zero tree Wavelet)**
- **SPIHT (Set Partitioning in Hierarchical Trees)**
- **STW (Spatial-orientation Tree Wavelet)**
- **WDR (Wavelet Difference Reduction)**
- **ASWDR (Adaptively Scanned Wavelet Difference Reduction)**

I use these methods in this thesis and also checked performance analysis in different situation. The basic scheme for compressing images is shown in Figure 1 below. Compression consists of two steps to generate a compressed bit stream.

FIGURE: A

FIGURE: B

FIGURE: C

FIGURE: D

FIGURE: DIFFERENT IMAGE WHICH WILL COMPRESS

FIGURE: 3-1: DIFFERENT IMAGE WHICH WILL COMPRESS

The rest step is a wavelet transform of the image and the second step is the compressed encoding of the image's wavelet transform. Decompression simply consists of reversing these two steps, decoding the compressed bit stream to produce an (approximate) image transform.

3.2 Working principle

In the block diagram the total procedure will discuss by flow chart

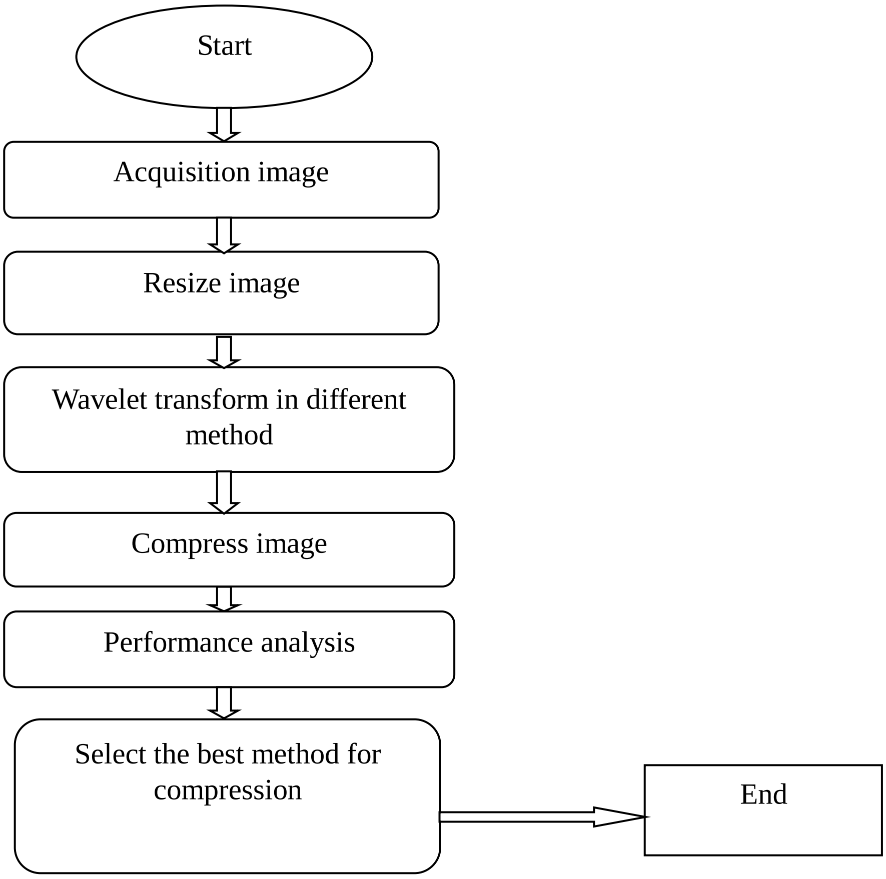

FIGURE: 3-2 BLOCK DIAGRAM OF PROCEDURE

- At first some image has been taken from the camera.
- Then it’s sent through the MATLAB basement and then resizes it to “512*512*3 “format because we know that for true compression, it is necessary to keep the size of rows and columns in the power of 2.
- Then take the Haar wavelet for compression then apply different types of method like as EZW, SPHIT, WDR, ASWDR, STW etc.
- Then It has been compared between different method and select the best method for compression here 4 photos are taken and then analyst it.

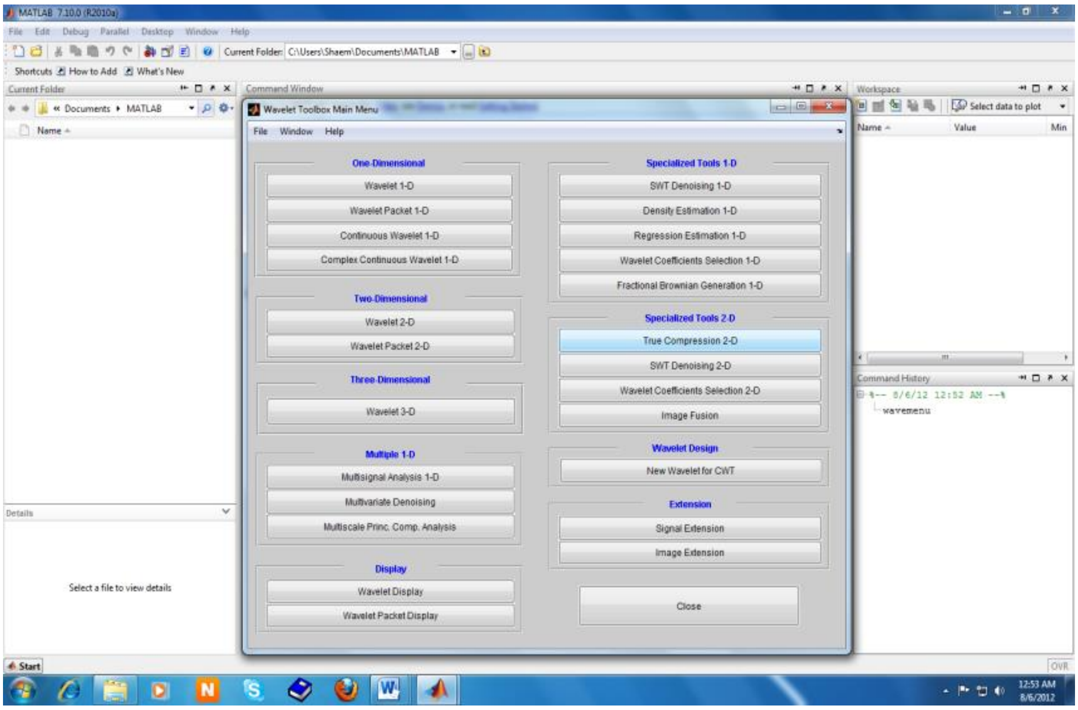

Figure: 3-3 Screen shot of the wavelet menu

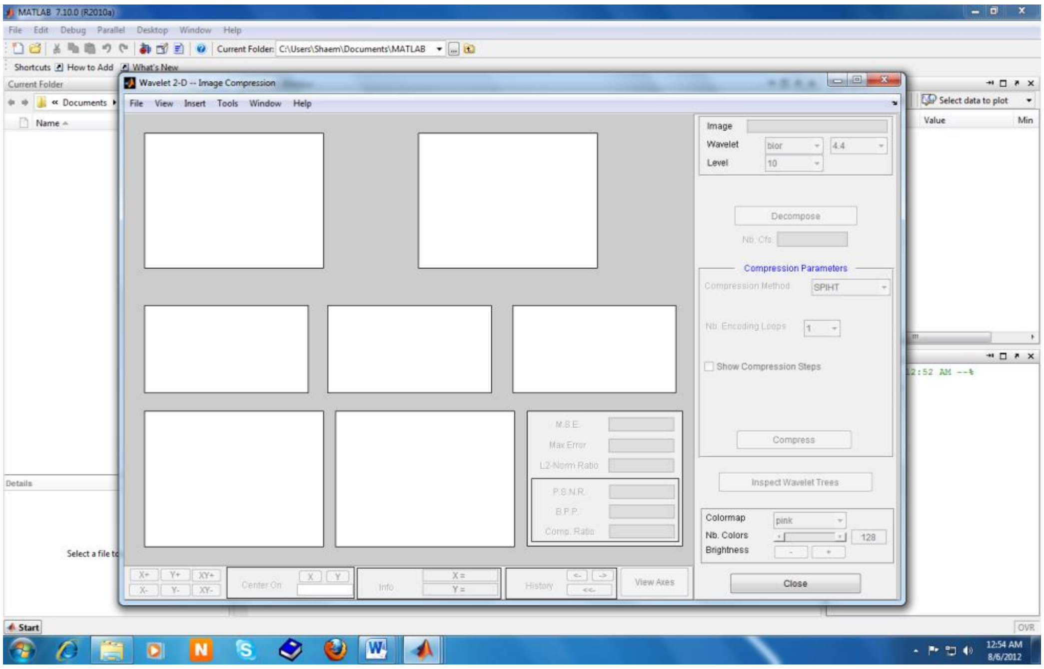

Figure: 3-4 MATLAB 2-D image compression interface

Wavelet-based coding provides substantial improvements in picture quality at higher compression ratios. Over the past few years, a variety of powerful and sophisticated wavelet-based schemes for image compression, as discussed later, have been developed and implemented. Because of the many advantages, wavelet-based compression algorithms are the suitable candidates for the new JPEG-2000 standard. This is lossy compression. In many cases, it is not necessary or even desirable that there be error-free reproduction of the original image. Lossy compression is also acceptable in fast transmission of still images over the Internet. Over the past few years, a variety of novel and sophisticated wavelet-based image coding schemes have been developed. These include Embedded Zero tree Wavelet (EZW), Set-Partitioning in Hierarchical Trees (SPIHT), Wavelet Difference Reduction (WDR), Adaptively Scanned Wavelet Difference Reduction (ASWDR), and STW. This list is by no means exhaustive and many more such innovative techniques are being developed. A few of these algorithms are briefly discussed here.

Chapter 4

Overall Performance Analysis

4. Introduction

In this chapter the overall performance analysis will discuss, using different wavelet method like as EZW, SPIHT, WDR, ASWDR and STW etc. Before starting the work, my purpose in discussing the baseline compression algorithm was to introduce some basic concepts, such as scan order, effects of different wavelet functions filter orders, number of decompositions, image contents and compression ratios, P.S.N.R, B.P.P were examined, which are needed for my examination of the algorithms to follow.

4.1 Embedded Zero tree Wavelet (EZW)

The EZW algorithm was one of the first algorithms to show the full power of wavelet-based image compression. It was introduced in the groundbreaking paper of Shapiro. An EZW encoder is an encoder specially designed to use with wavelet transforms. The EZW encoder is based on progressive encoding to compress an image into a bit stream with increasing accuracy

The EZW encoder is based on *two* important observations:

- Natural images in general have a low pass spectrum. When an image is wavelet transformed the energy in the sub bands decreases as the scale decreases (low scale means high resolution), so the wavelet coefficients will, on average, be smaller in the higher sub bands than in the lower sub bands. These shows that progressive encoding is a very natural choice for compressing wavelet transformed images, since the higher sub bands only add detail.

- Large wavelet coefficients are more important than small wavelet coefficients. These two observations are exploited by encoding the wavelet coefficients in decreasing order, in several passes. In the table 1 we show the result of compression ratio using EZW algorithm for 4 images A, B, C and D of size

512*512*3. EZW encoder does not really compress anything; it only reorders wavelet coefficients in such a way that they can be compressed very efficiently.

Features of EZW:

- Better performance than the other method.
- Employs progressive and embedded transmission.
- Uses zero tree concept
- Tree coded with single symbol
- Used predefined scanning order
- Good result without pre-stored tables codebooks, training.

Demerits of EZW:

- Transmission of coefficient position is missing
- No real compress-ion
- Followed by arithmetic encoder

TABLE-1: Compression ratio Bit per pixel and PSNR Result for 512*512*3 image.

size	Level	CR	PSNR	BPP
512*512	2	81.58	58.69	6.528
512*512	2	89.04	59.76	7.1232
512*512	2	58.07	51.95	4.6458
512*512	2	74.17	57.85	5.93

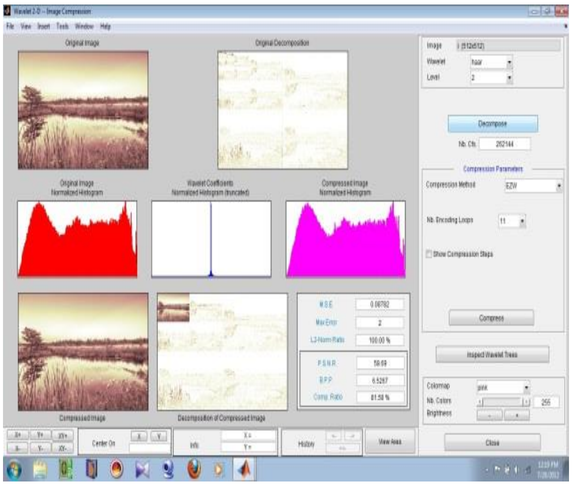

Figure: EZW compression for A image

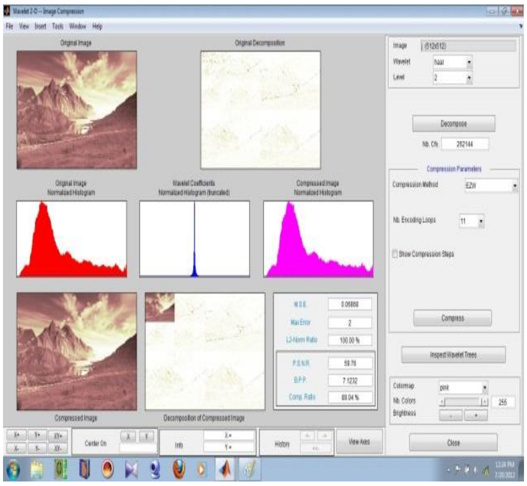

Figure: EZW compression for B image

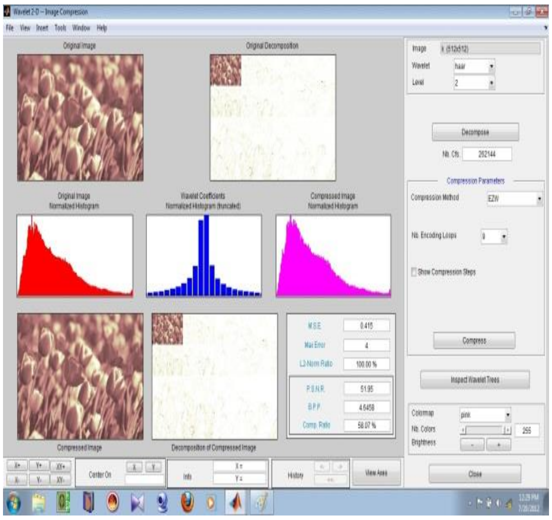

Figure: EZW compression for C image

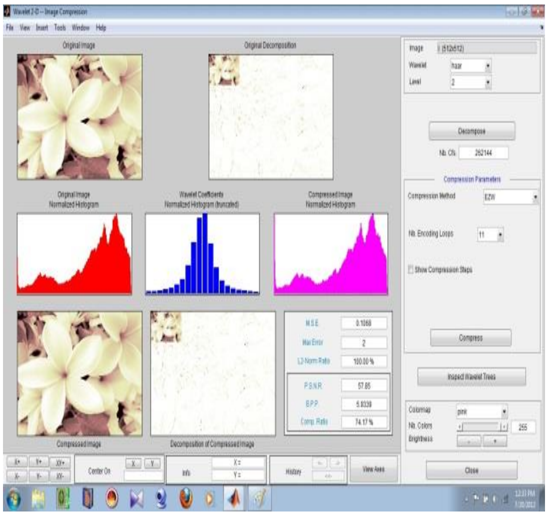

Figure: EZW compression for D image

Figure: 4-1 Compress screenshot of four images using in EZW method

4.2 Set Partitioning in Hierarchical Trees (SPIHT)

SPIHT is a wavelet-based image compression coder. It first converts the image into its wavelet transform and then transmits information about the wavelet coefficients. The decoder uses the received signal to reconstruct the wavelet and performs an inverse transform to recover the image. We selected SPIHT because SPIHT and its predecessor, the embedded zero tree wavelet coder, were significant breakthroughs in still image compression in that they offered significantly improved quality over vector quantization, JPEG, and wavelets combined with quantization, while not requiring training and producing an embedded bit stream. SPIHT displays exceptional characteristics over several properties all at once [12] including:

- Good image quality with a high PSNR ·
- Fast coding and decoding ·
- A fully progressive bit -stream ·
- Can be used for lossless compression ·
- May be combined with error protection ·

TABLE-2: Compression ratio Bit per pixel and PSNR Result for (512*512*3) image.

size	Level	CR	PSNR	BPP
512*512	2	46.71	38.87	3.737
512*512	2	47.53	39.32	3.8028
512*512	2	39.16	39.9	3.13
512*512	2	35.73	40.74	2.8585

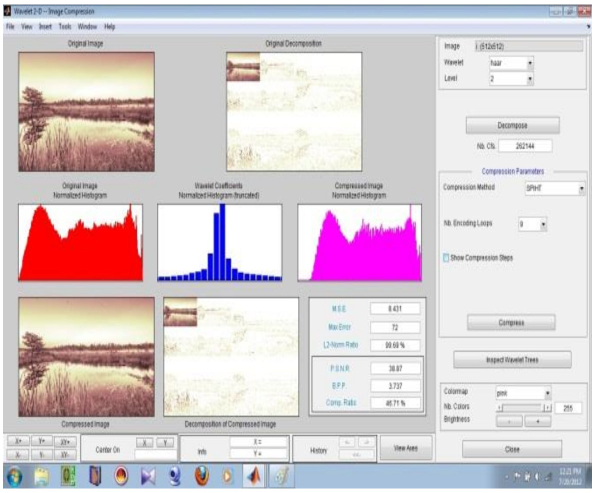

FIGURE: SPIHT COMPRESSION FOR A IMAGE

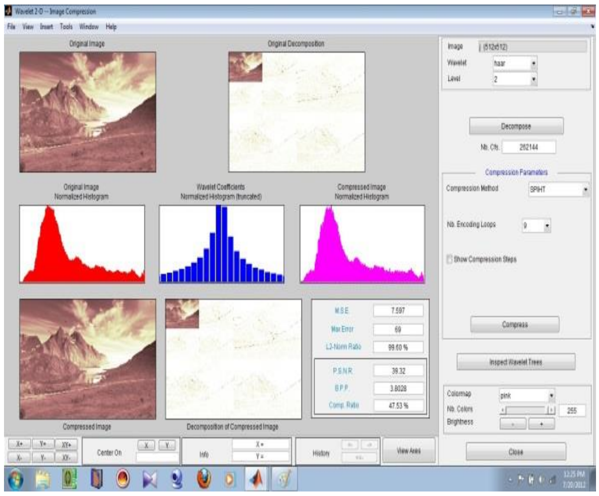

FIGURE: SPIHT COMPRESSION FOR B IMAGE

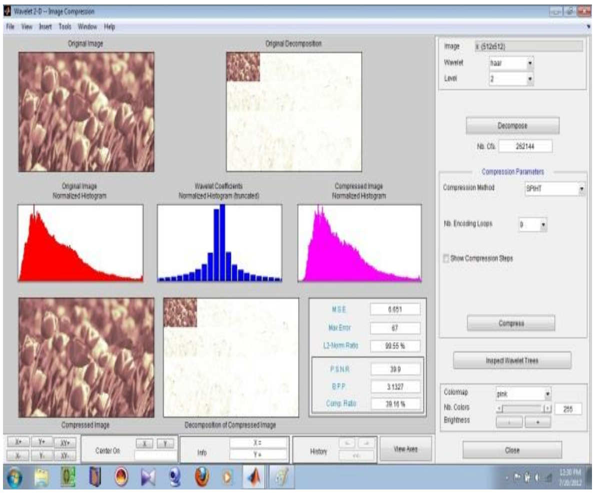

FIGURE: SPIHT COMPRESSION FOR C IMAGE

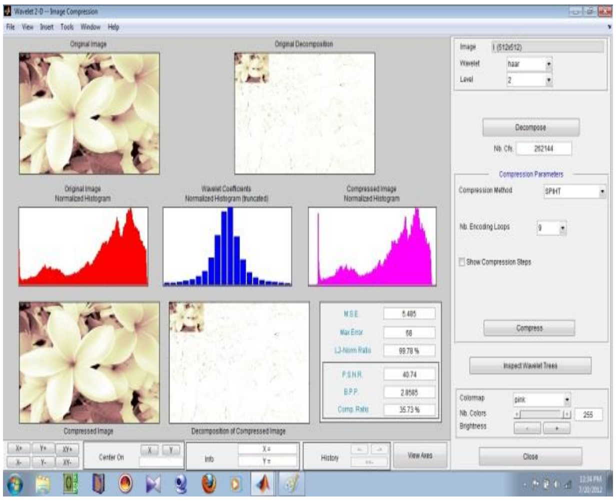

FIGURE: SPIHT COMPRESSION FOR D IMAGE

Figure: 4-2 Compress screenshot of four images using in SPIHT method

Discrete Wavelet Transform (DWT) runs a high and low-pass filter over the signal in one dimension. The result is a new image comprising of a high and low-pass sub band. The next wavelet level is calculated by repeating the horizontal and vertical transformations on the low-pass sub band from the previous level. The DWT repeats this procedure for however many levels are required. Each procedure is fully reversible (within the limits of fixed precision) so that the original image can be reconstructed from the wavelet transformed image. SPIHT is a method of coding and decoding.[14]

Demerits of SPIHT:

- Only implicitly locates position of significant coefficient
- More memory required due to 3 lists
- Suites variety of natural images

4.3 Wavelet Difference Reduction (WDR)

One of the defects of SPIHT is that it only implicitly locates the position of significant coefficients. This makes it difficult to perform operations which depend on the position of significant transform values, such as region selection on compressed data. Region selection, also known as region of interest (ROI), means a portion of a compressed image that requires increased resolution.

The only difference between WDR and bit-plane encoding is the significant pass. In WDR, the output from the significance pass consists of the signs of significant values along with sequences of bits which concisely describe the precise locations of significant values [1].

Features of WDR:

- Uses ROI concept
- Introduced by Tian and Wells.
- Better perceptual image quality than SPIHT
- No searching through quad trees as in SPIHT
- Less complex then SPIHT
- Better preservation of edges than SPIHT

Demerits of WDR:

- PSNR is not higher than SPIHT.

TABLE-3: Compression ratio Bit per pixel and PSNR Result for (512*512*3) image.

size	Level	CR	PSNR	BPP
512*512	2	80.02	40.16	6.4012
512*512	2	89.14	41.33	7.131
512*512	2	67.23	41.61	5.37
512*512	2	62.00	42.84	4.95

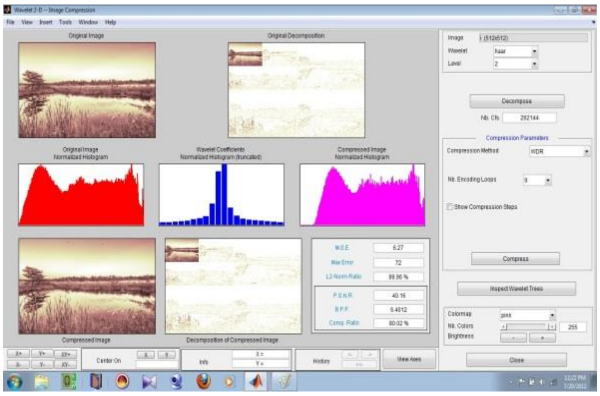

FIGURE: WDR COMPRESSION FOR A IMAGE

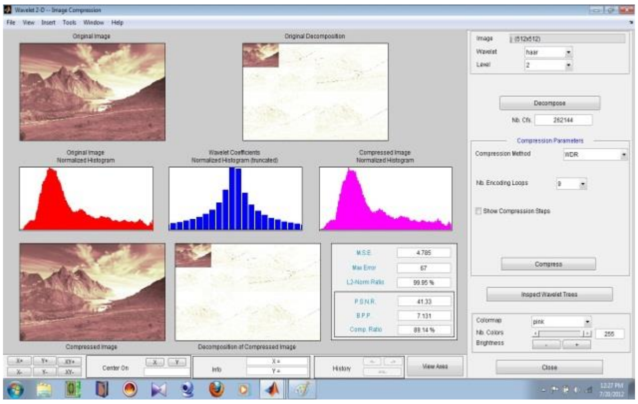

FIGURE: WDR COMPRESSION FOR B IMAGE

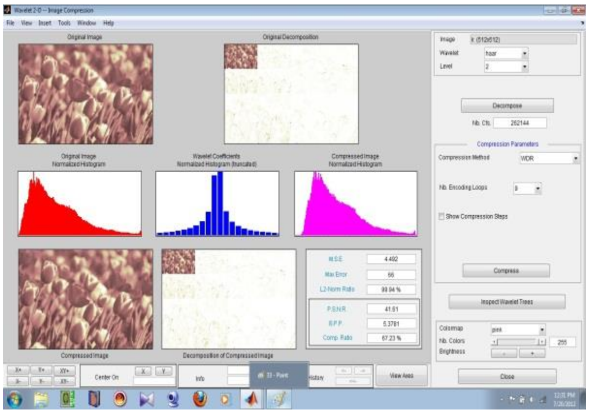

FIGURE: WDR COMPRESSION FOR C IMAGE

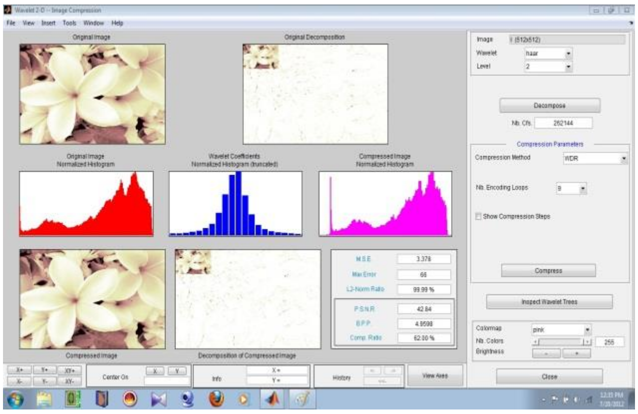

FIGURE: WDR COMPRESSION FOR D IMAGE

Figure: 4-3 Compress screenshot of four images using in WDR method

4.4 Adaptively Scanned Wavelet Difference Reduction (ASWDR)

The ASWDR algorithm aims to improve the subjective perceptual qualities of compressed images and improve this result of objective distortion measures. We shall treat two distortion measures, PSNR and edge correlation, which we shall define in the section or experimental results. PSNR is a commonly used measure of error, while edge correlation is a measure that we have found useful in quantifying the preservation of edge details in compressed images, and seems to correspond well to subjective impressions of the perceptual quality of the compressed images. [21]

High compression ratio images are used in reconnaissance and in medical applications, where fast transmission and ROI are employed, as well as multi-resolution detection. Table-6 shows the improved PSNR values for ASWDR compared to WDR. The WDR and ASWDR algorithms do allow for ROI while SPIHT does not. Furthermore, their superior performance in displaying edge details at low bit rates facilitates multi-resolution detection.

Features of ASWDR:

- Modified scanning order compared to WDR
- Prediction of locations of new significant values
- Dynamically adapts to the locations of edge details
- Encodes more significant values than WDR.

TABLE-4: Compression ratio Bit per pixel and PSNR Result for (512*512*3) image.

size	Level	CR	PSNR	BPP
512*512	2	76.22	40.16	6.0975
512*512	2	84.64	41.33	6.7708
512*512	2	62.88	41.61	5.0306
512*512	2	59.27	42.84	4.7419

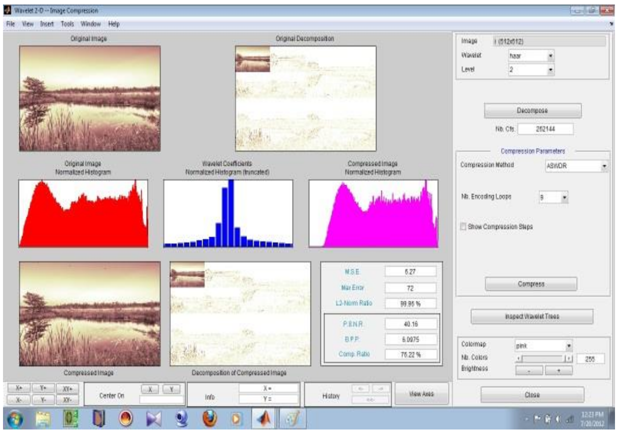

FIGURE: ASWDR COMPRESSION FOR A IMAGE

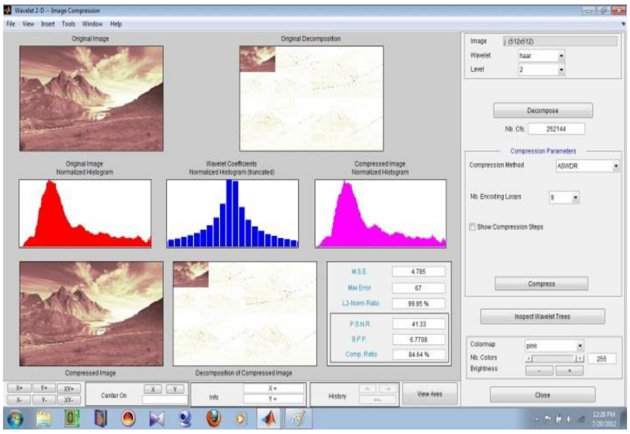

FIGURE: ASWDR COMPRESSION FOR B IMAGE

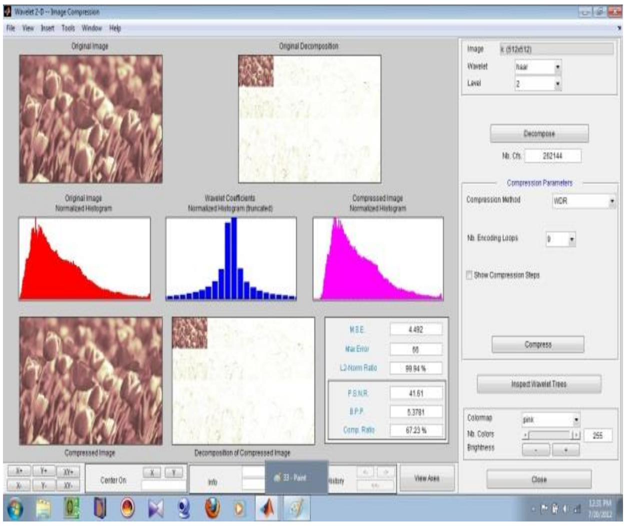

FIGURE: ASWDR COMPRESSION FOR C IMAGE

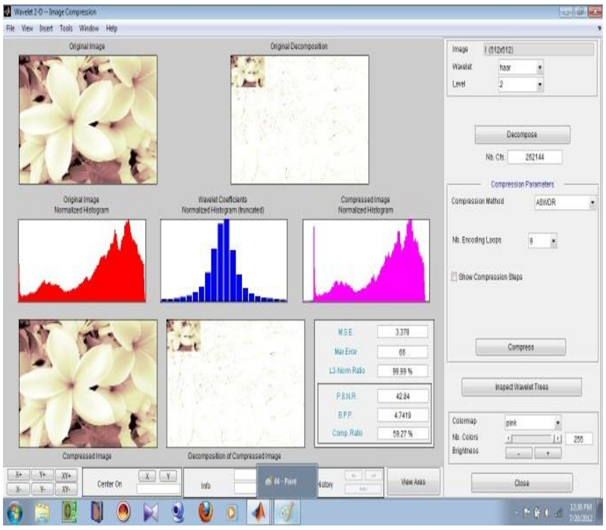

FIGURE: ASWDR COMPRESSION FOR D IMAGE

Figure: 4-4 Compress screenshot of four images using in ASWDR method

4.5 Spatial-orientation Tree Wavelet (STW)

STW is essentially for the SPIHT algorithm. The only difference is that SPIHT is slightly more careful in its organization of coding output.

Second, we describe the SPIHT algorithm. It is easier to explain SPIHT using the concepts underlying STW. Third, we see how well SPIHT compresses images. The only difference between STW and EZW is that STW uses a different approach to encoding the zero tree information. STW uses a state transition model. From one threshold to the next, the locations of transform values undergo state transitions. This model allows STW to reduce the number of bits needed for encoding. Instead of code for the symbols R and I output by EZW to mark locations, the STW algorithm uses states IR, IV , SR, and SV and outputs code for state-transitions such as IR $\rightarrow$ IV , SR $\rightarrow$ SV , etc.

TABLE-5: Compression ratio Bit per pixel and PSNR Result for (512*512*3) image.

size	Level	CR	PSNR	BPP
512*512	2	54.37	47.52	4.3497
512*512	2	58.55	45.91	4.68
512*512	2	41.87	46.53	3.34
512*512	2	37.74	45.45	3.019

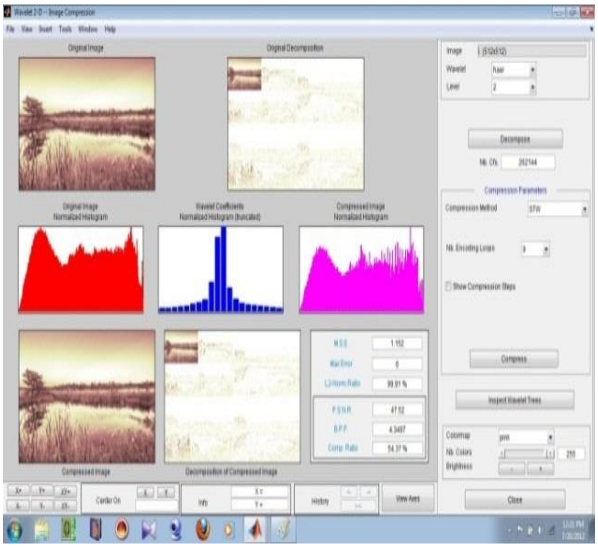

FIGURE: STW COMPRESSION FOR A IMAGE

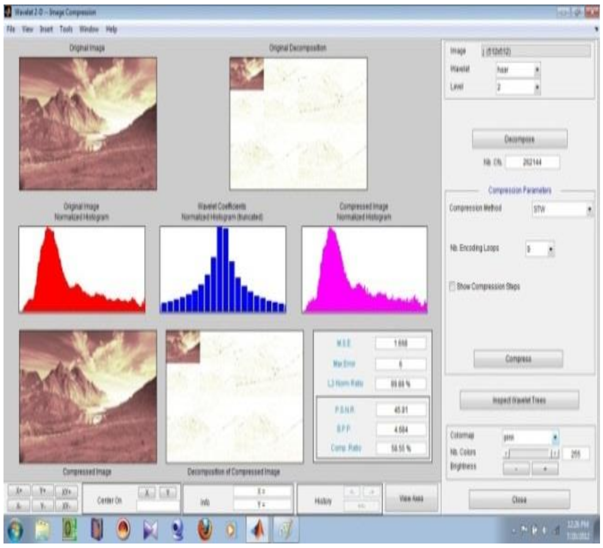

FIGURE: STW COMPRESSION FOR B IMAGE

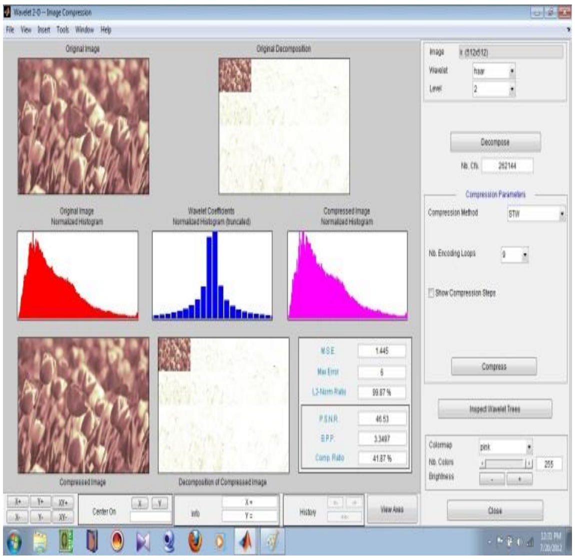

FIGURE: STW COMPRESSION FOR C IMAGE

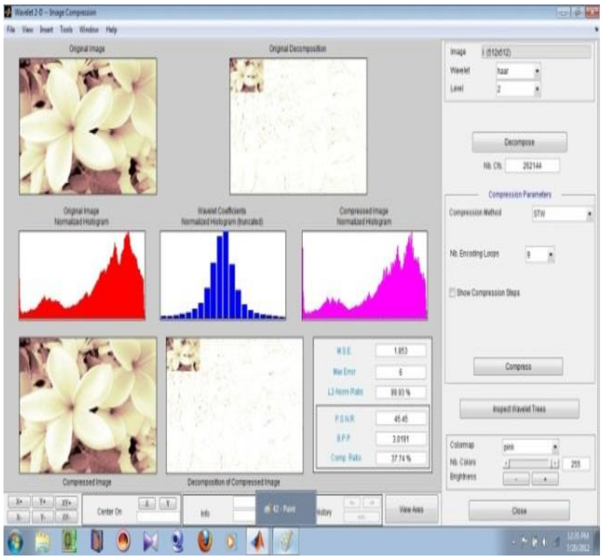

FIGURE: STW COMPRESSION FOR D IMAGE

Figure: 4-5 Compress screenshot of four images using in STW method

Chapter 5

Simulation and Result

In this report it have been said that the overall performance of the four images are shown in the below table. Here we have been said that, in case of EZW method MSE is 0.0868 & PSNR is 58 & BPP is 6.5267. For SPIHT method, MSE is 7.04 & PSNR is 39.50 & BPP is 3.379. For STW method, MSE is 1.6& PSNR is 45.91 & BPP is 3.84. For WDR method, MSE is 4.72& PSNR is 41.29& BPP is5.97. For ASWDR method, MSE is 4.752 & PSNR is 41.49 & BPP is5.660.Among all these methods, EZW are best performed though STW is averagely good as compared to the other method.

TABLE-6: Total Analytical Result for (512*512*3) image.

	EZW (a,b,c,d)	SPIHT (a,b,c,d)	STW (a,b,c,d)	WDR (a,b,c,d)	ASWDR (a,b,c,d)
M.S.E	0.08782	8.431	1.152	6.27	6.27
	0.6868	7.597	1.668	4.785	4.875
	0.415	6.651	1.445	4.492	4.492
	0.1068	5.485	1.853	3.378	3.378
P.S.N.R	58.69	38.87	47.52	41.33	40.16
	59.76	39.32	45.91	39.38	41.33
	51.95	39.1	46.53	41.61	41.61
	57.85	40.74	45.45	42.84	42.84
B.P.P	6.5267	3.737	4.3497	6.4012	6.0975
	7.1232	3.8028	4.684	7.131	6.7708
	4.6458	3.1327	3.3497	5.3781	5.0306
	5.9339	2.8585	3.0191	4.9598	4.7419

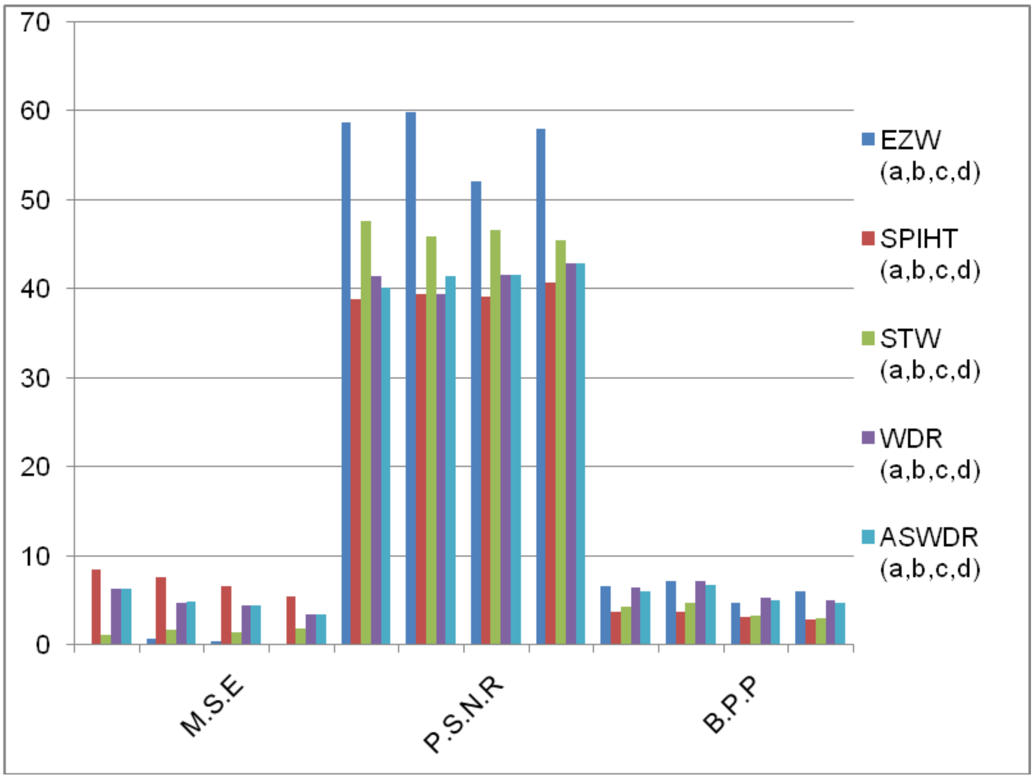

Figure: 5-1 Graph 1(For total analytical result)

The graph 1 represents that the overall performance for different method. Here it has been seen that among the five methods, EZW perform better than other method here MSE of EZW method is lower and peak signal to noise ratio is higher than the other method. The below table state that the average performance for five method here different types of parameter like as compression ratio, Peak signal to noise ratio and Bit per pixel have been discussed.

TABLE-7: Average Result for 4 (512*512*3) image.

	WDR	ASWDR	EZW	SPIHT	STW
CR	74.597	70.7525	75.715	42.29075	48.1325
PSNR	41.485	41.485	57.0625	39.5075	41.29
BPP	5.963	5.6602	6.0574	3.38275	3.850625
MSE	4.73125	4.73125	0.324105	7.041	1.5295

Figure: 5-2Graph 2 (For BPP vs.MSE)

In this graph represents that the average compares between Bit per pixel and Mean square error for different method .here it have been seen that for EZW method the mean square error is lesser then the another method where the Bit per pixel is medium.

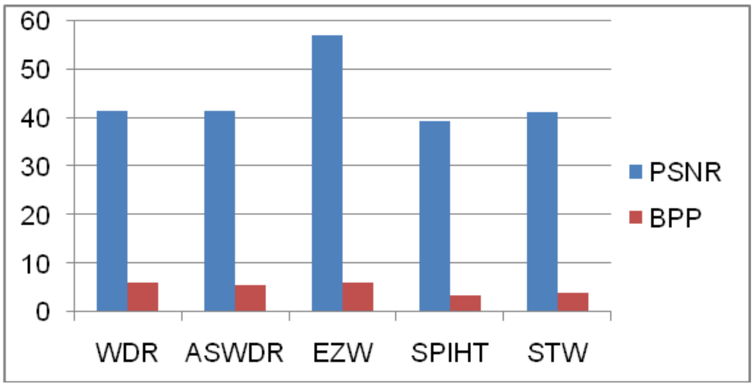

Figure: 5-3Graph 3 (For BPP vs. PSNR)

In the graph 3 two types of parameter have been discussed and compare between them here it has been seen that the peak signal to noise ratio is higher than the others method where the Bit per pixel is lower

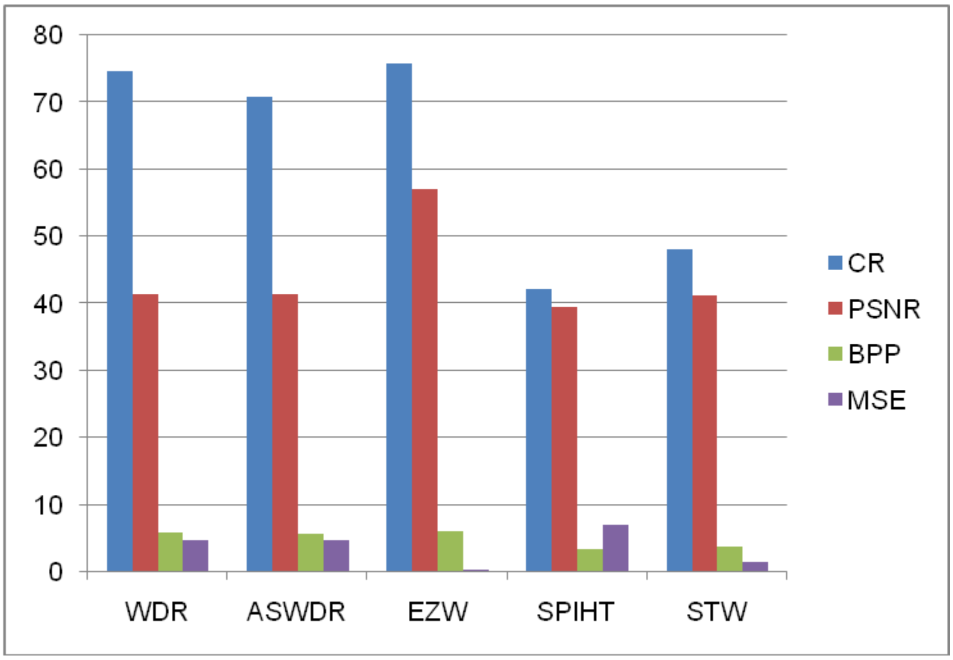

Figure: 5-4 Graph 4 (Overall performance for CR, PSNR, BPP, MSE)

In the graph 4 represents that the overall performance for CR, PSNR, BPP, MSE. And it have been seen that for EZW method BPP is lower where PSNR is higher than the other method so in case of the total overall performance analysis it has been said that EZW perform better than other.

5.1 MATLAB SIMUTATION

The figure5-5 shows B.P.P VS. MSE The simulation result of the graph represents that EZW performed best among all other method .Here B.P.P & M.S.E is less for EZW and all the other method does not perform as well.

The Figure 5-6 shows B.P.P VS PSNR The simulation result of the second graph represents that EZW is perform best as compared to other method. Here B.P.P is less as well M.S.E. is less that time P.S.N.R is high and it shows maximum output performance.

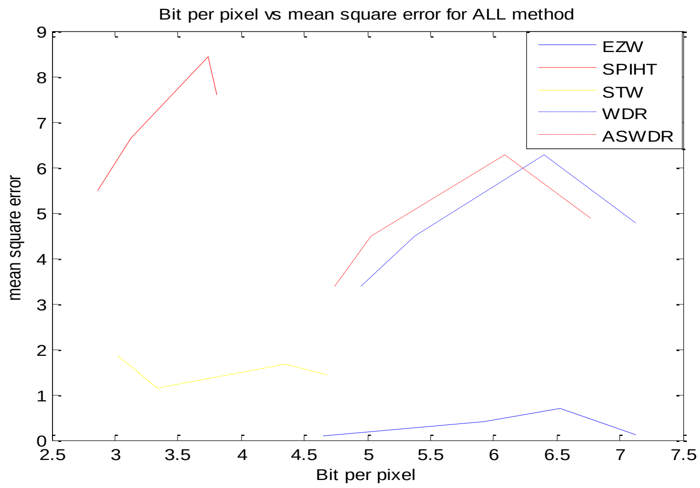

Figure 5-5: Bit per Pixel vs. Mean Square error.

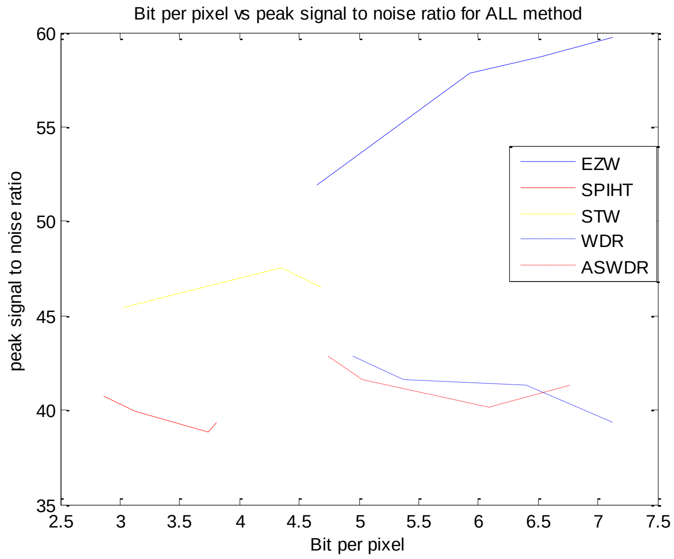

Figure 5-6: Bitper Pixel vs. Peak Signal to Noise Ratio.

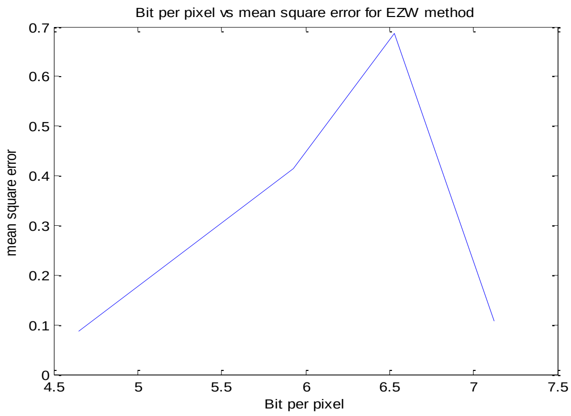

Figure: BPP vs. MSE for EZW Method.

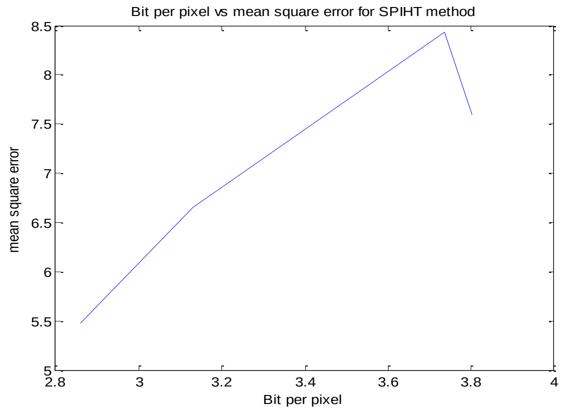

Figure: BPP vs. MSE for SPIHT Method.

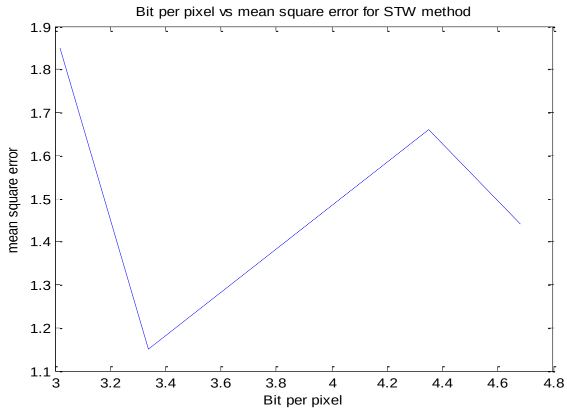

Figure: BPP vs. MSE for STW Method.

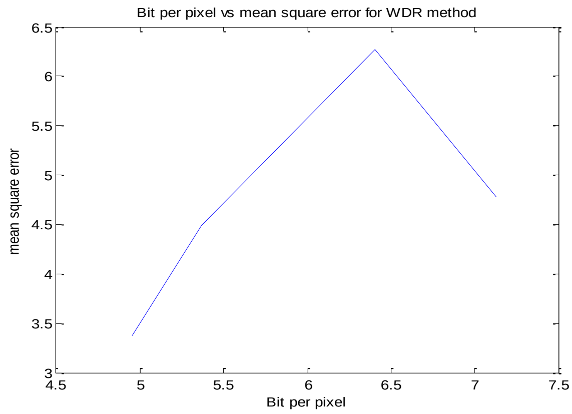

Figure: BPP vs. MSE for WDR Method.

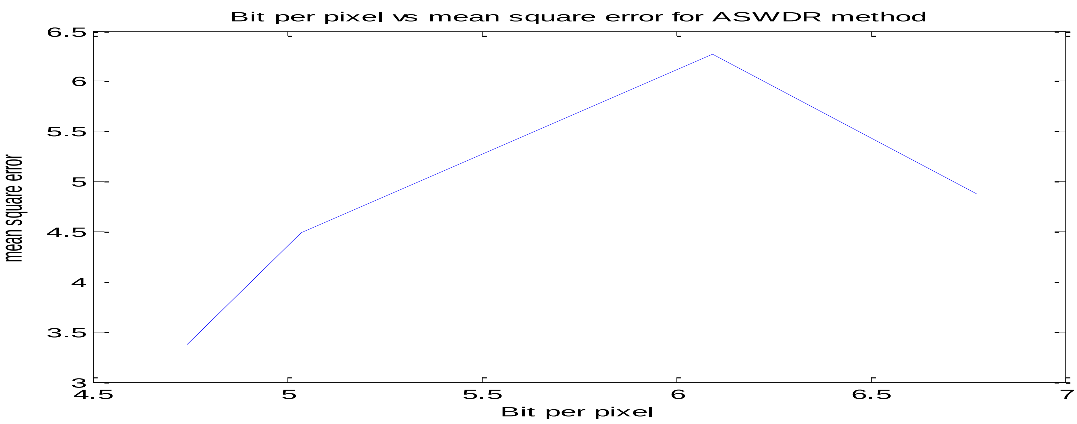

Figure: BPP vs. MSE for

Figure:5-8: Graphical representation of BPP vs. MSE for all Methods

In the figure it have been seen that BPP vs. MSE compares where in 4.5 to 6 BPP the MSE is lower in EZW method but other method its higher up to 9.5 where EZW method the MSE Is .08 to 1.5.

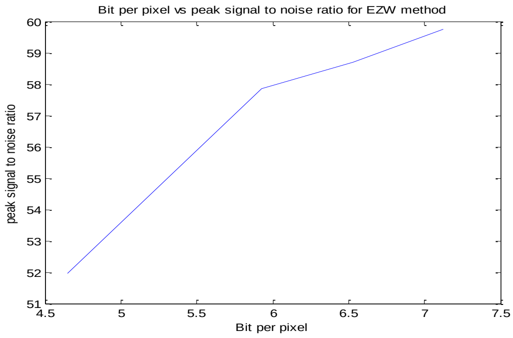

Figure: BPP vs. PSNR for EZW

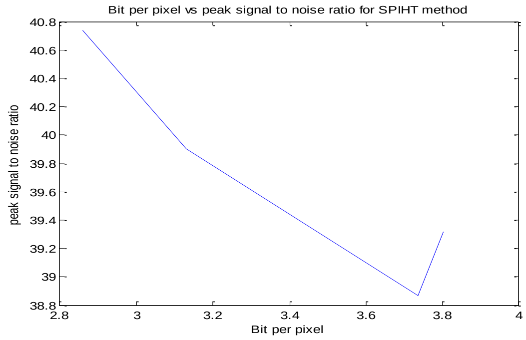

Figure: BPP vs. PSNR for SPIHT

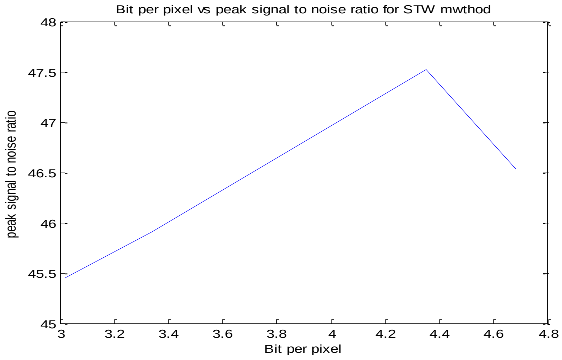

Figure: BPP vs. PSNR for STW

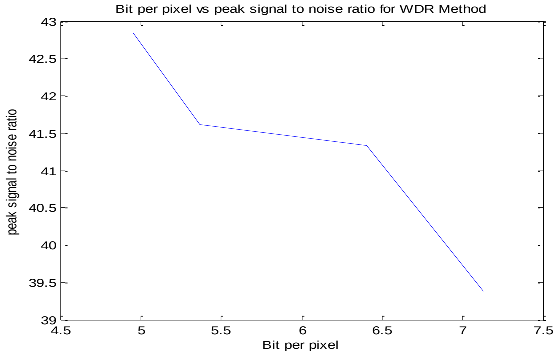

Figure: BPP vs. PSNR for WDR

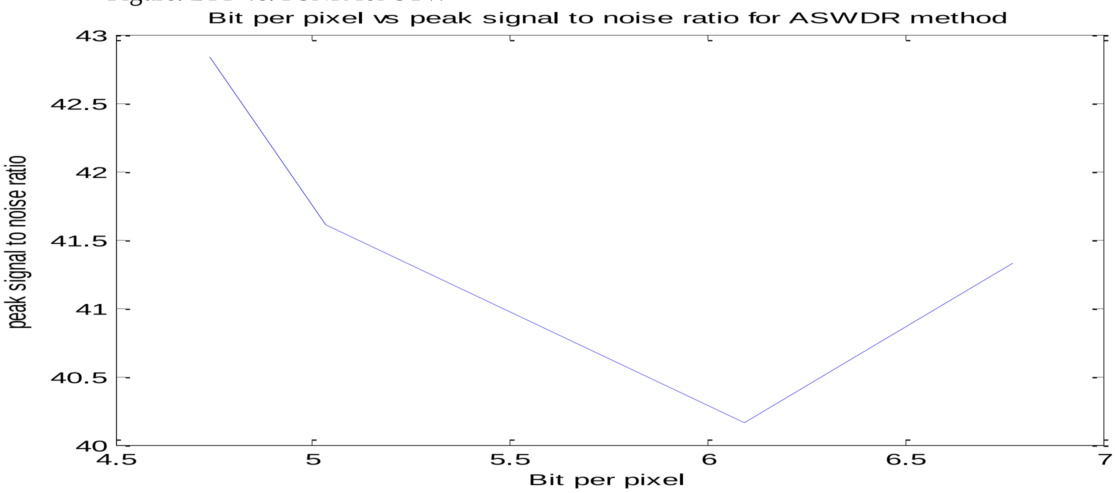

Figure: BPP vs. PSNR for ASWDR

Figure 5-9: Graphical representation of BPP vs. PSNR for all methods

The figure represents that the Bit per Pixel vs. Peak signal to noise ratio in different method. Here it have been seen that for EZW method is performed from 4.5 to 6 the PSNR is higher and it almost 58.44.In case of other method we see for 4.5 to 6 BPP the PSNR not more than 45 .so Here the individual EZW method perform better.

5.2 Discussion

From the analysis it have been seen that, the various features of the main coding schemes are summarized. The latest coding techniques such as EZW perform better than the other method. Here we see that from the EZW method we can get the maximum peak signal to noise ratio and low Bit per pixel.

TYPE	FEATURES	DEMERITS
EZW	• Better performance than the other method. • Employs progressive and embedded transmission. • Uses zero tree concept • Tree coded with single symbol • Used predefined scanning order • Good result without pre-stored tables codebooks, training.	• Transmission of coefficient position is missing • No real compress-ion • Followed by arithmetic encoder.
SPIHT	• Widely used-high PSNR values for given CRs for variety of images • Employs spatial orientation tree structure • Employs progressive and embedded transmission	• Only implicitly locates position of significant coefficient • More memory required due to 3 lists • Suites variety of natural images

WDR	• Uses ROI concept • Introduced by Tian and Wells • Better perceptual image quality than SPIHT • No searching through quad trees as in SPIHT • Less complex then SPIHT • Better preservation of edges than SPIHT	• PSNR is not higher than SPIHT.
ASWDR	• Modified scanning order compared to WDR • Prediction of locations of new significant values • Dynamically adapts to the locations of edge details • Encode s more significant values than WDR • PSNR better than SPIHT and WDR • Perceptual image quality is better than WDR • Slightly higher edge correlation values than WDR • Preserves more of the fine Details.	

Chapter 6

Conclusion & Future Scope

6.1 Conclusion

In this paper, the results were compared for the different wavelet-based image compression techniques. The effects of different wavelet functions filter orders, number of decompositions, image contents and compression ratios were examined. The results of the above techniques WDR, ASWDR, STW, SPIHT, EZW etc., were compared by using the parameters such as PSNR, MSE BPP values from the reconstructed image. These techniques are successfully tested in many images. The experimental results show that the EZW technique performs better than the WDR & other method in terms of the performance parameters and coding time with acceptable image quality. From the experimental results, it is identified that the PSNR values from the compressed images by using EZW compression is higher than other compression. And also it is shown that the MSE values from the reconstructed images by using EZW compression are lower than other compression. Finally, it is identified that EZW compression performs better when compare to WDR, ASWDR and other compression.

6.2 Future scope:

In this thesis I just only show the performance analysis of image compression using wavelet method. In the future I will study about the decompression of image and then reconstruct the original image from the compressed image keeping the same Quality of the image.

Appendix A

ASWDR	Adaptively Scanned Wavelet Difference Reduction
EZW	Embedded Zero tree Wavelet
SPIHT	Set Partitioning in Hierarchical Trees
STW	Spatial-orientation Tree Wavelet
WDR	Wavelet Difference Reduction
PSNR	Peak Signal to Noise Ratio
BPP	Bit per Pixel
MSE	Mean Square Error
CR	Compression Ratio
NR	Normalized Ratio
FFT	Fast Fourier Transform
DWT	Discrete Wavelet Transform

Appendix B

MATLAB CODING:

```
%%EZW
cr1=[58.07  74.17 81.58 89.04 ];
psnr1=[51.95 57.85 58.69 59.76 ];
bpp1=[4.6458 5.93 6.528 7.1232 ];
mse1=[.08782 .415 .6868 .1068];

%%SPIHT
cr2=[46.71 47.53 39.16 39.73];
psnr2=[40.74 39.9 38.87 39.32 ];
bpp2=[2.8585 3.13 3.737 3.8028 ];
mse2=[5.48 6.65 8.43 7.59 ];

%%STW
cr3=[54.37 58.55 41.87 37.74];
psnr3=[45.45 45.91 47.52  46.53 ];
bpp3=[3.019 3.34 4.3497 4.68  ];
mse3=[1.85 1.15 1.66 1.44 ];


%%%WDR
cr4=[80.02 89.14 67.23 62.00];
psnr4=[42.84 41.61 41.33 39.38  ];
bpp4=[4.95 5.37 6.4012 7.131  ];
mse4=[3.37 4.49 6.27 4.78 ];

%%ASWDR
cr5=[76.22 84.64 62.88 59.27];
psnr5=[42.84 41.61 40.16 41.33 ];
bpp5=[4.7419 5.0306 6.09 6.7708  ];
mse5=[3.378 4.492 6.27 4.875 ];


%subplot(3,1,1)
title('mean square error vs peak signal to noise ratio for ALL method')
plot(bpp1,mse1)
%title('mean squire error vs peak signal to noise ratio')
xlabel('Bit per pixel')
ylabel('Mean square error')

%subplot(3,1,2)
```

```
hold on

plot(bpp2,mse2,'r')
hold on
%subplot(3,2,1)

plot(bpp3,mse3,'y')

hold on
%subplot(3,2,2)

plot(bpp4,mse4,'--b')

hold on

plot(bpp5,mse5,'--r')

hold off

figure
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%


title('mean square error vs peak signal to noise ratio for EZW method')
plot(mse1,psnr1)
%title('mean squire error vs peak signal to noise ratio')
%xlabel('mean square error')
%ylabel('peak signal to noise ratio')
hold on
%subplot(3,1,2)

plot(mse2,psnr2,'r')
hold on

plot(mse3,psnr3,'y')
hold on
%subplot(3,2,2)

plot(mse4,psnr4,'--b')
hold on

%subplot(3,3,1)

plot(mse5,psnr5,'--r')
title('mean square error vs peak signal to noise ratio for ALL method')
xlabel('mean square error')
ylabel('peak signal to noise ratio')
```

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

figure
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%


title('Bit per pixel vs peak signal to noise ratio for ALL method')
plot(bpp1,psnr1)
%title('mean squire error vs peak signal to noise ratio')
%xlabel('mean square error')
%ylabel('peak signal to noise ratio')
hold on

%subplot(3,1,2)

plot(bpp2,psnr2,'r')
hold on

plot(bpp3,psnr3,'y')
hold on

%subplot(3,2,2)

plot(bpp4,psnr4,'--b')
hold on

%subplot(3,3,1)

plot(bpp5,psnr5,'--r')
title('Bit per pixel vs peak signal to noise ratio for ALL method')
xlabel('Bit per pixel')
ylabel('peak signal to noise ratio')
```

BPP VS MSE

```
%%EZW
cr1=[58.07  74.17 81.58 89.04 ];
psnr1=[51.95 57.85 58.69 59.76 ];
bpp1=[4.6458 5.93 6.528 7.1232 ];
mse1=[.08782 .415 .6868 .1068];

%%SPIHT
cr2=[46.71 47.53 39.16 39.73];
psnr2=[40.74 39.9 38.87 39.32 ];
bpp2=[2.8585 3.13 3.737 3.8028 ];
mse2=[5.48 6.65 8.43 7.59 ];

%%STW
cr3=[54.37 58.55 41.87 37.74];
psnr3=[45.45 45.91 47.52  46.53 ];
bpp3=[3.019 3.34 4.3497 4.68  ];
mse3=[1.85 1.15 1.66 1.44 ];




%%%WDR
cr4=[80.02 89.14 67.23 62.00];
psnr4=[42.84 41.61 41.33 39.38  ];
bpp4=[4.95 5.37 6.4012 7.131  ];
mse4=[3.37 4.49 6.27 4.78 ];
%%ASWDR
cr5=[76.22 84.64 62.88 59.27];
psnr5=[42.84 41.61 40.16 41.33 ];
bpp5=[4.7419 5.0306 6.09 6.7708  ];
mse5=[3.378 4.492 6.27 4.875 ];
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%



%subplot(3,1,1)
plot(bpp1,mse1)
title('Bit per pixel vs mean square error for EZW method')

%title('mean squire error vs peak signal to noise ratio')
xlabel('Bit per pixel')
ylabel('mean square error')
figure
%subplot(3,1,2)
```

```
plot(bpp2,mse2)
title('Bit per pixel vs mean square error for SPIHT method')
xlabel('Bit per pixel')
ylabel('mean square error')
figure
%subplot(3,2,1)

plot(bpp3,mse3)
title('Bit per pixel vs mean square error for STW method')
xlabel('Bit per pixel')
ylabel('mean square error')
figure
%subplot(3,2,2)

plot(bpp4,mse4)
title('Bit per pixel vs mean square error for WDR method')
xlabel('Bit per pixel')
ylabel('mean square error')
figure
%subplot(3,3,1)

plot(bpp5,mse5)
title('Bit per pixel vs mean square error for ASWDR method')
xlabel('Bit per pixel')
ylabel('mean square error')
```

BPP VS PSNR

```
%%EZW
cr1=[58.07  74.17 81.58 89.04 ];
psnr1=[51.95 57.85 58.69 59.76 ];
bpp1=[4.6458 5.93 6.528 7.1232 ];
mse1=[.08782 .415 .6868 .1068];

%%SPIHT
cr2=[46.71 47.53 39.16 39.73];
psnr2=[40.74 39.9 38.87 39.32 ];
bpp2=[2.8585 3.13 3.737 3.8028 ];
mse2=[5.48 6.65 8.43 7.59 ];

%%STW
cr3=[54.37 58.55 41.87 37.74];
psnr3=[45.45 45.91 47.52  46.53 ];
bpp3=[3.019 3.34 4.3497 4.68  ];
mse3=[1.85 1.15 1.66 1.44 ];




%%%WDR
cr4=[80.02 89.14 67.23 62.00];
psnr4=[42.84 41.61 41.33 39.38  ];
bpp4=[4.95 5.37 6.4012 7.131  ];
mse4=[3.37 4.49 6.27 4.78 ];
%%ASWDR
cr5=[76.22 84.64 62.88 59.27];
psnr5=[42.84 41.61 40.16 41.33 ];
bpp5=[4.7419 5.0306 6.09 6.7708  ];
mse5=[3.378 4.492 6.27 4.875 ];
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%


%%%%%%%EZW METHOD%%%%%%%%%%%%%%%%%%%%%%%%
%subplot(3,1,1)
plot(bpp1,psnr1)
title('Bit per pixel vs peak signal to noise ratio for EZW method')

%title('mean squire error vs peak signal to noise ratio')
xlabel('Bit per pixel')
ylabel('peak signal to noise ratio')
figure
%subplot(3,1,2)
```

```
plot(bpp2,psnr2)
title('Bit per pixel vs peak signal to noise ratio for SPIHT method')
xlabel('Bit per pixel')
ylabel('peak signal to noise ratio')
figure
%subplot(3,2,1)

plot(bpp3,psnr3)
title('Bit per pixel vs peak signal to noise ratio for STW mwthod')
xlabel('Bit per pixel')
ylabel('peak signal to noise ratio')
figure
%subplot(3,2,2)

plot(bpp4,psnr4)
title('Bit per pixel vs peak signal to noise ratio for WDR Method')
xlabel('Bit per pixel')
ylabel('peak signal to noise ratio')
figure
%subplot(3,3,1)

plot(bpp5,psnr5)
title('Bit per pixel vs peak signal to noise ratio for ASWDR method')
xlabel('Bit per pixel')
ylabel('peak signal to noise ratio')
```

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