IMAGE COMPRESSION BASED ON IMPROVED SPIHT AND REGION OF INTEREST

A thesis submitted in partial fulfillment of the requirements for the award of degree of

Master of Technology

in

VLSI Design & CAD

Submitted By:

Sandeep Kumar

Roll No. 600961018

Under the Guidance of

Dr. Sanjay Sharma

Associate Professor

Department of Electronics & Communication Engineering

Thapar University, Patiala

June 2011

CERTIFICATE

I hereby declare that the work which is being presented in the thesis entitled, "**Image Compression Based on Improved SPIHT and Region of Interest**" in partial fulfillment of the requirement for the award of degree of M.Tech. (VLSI Design & CAD) at Electronics and Communication Engineering Department of Thapar University, Patiala, is an authentic record of my own work carried out under the supervision of Dr. Sanjay Sharma, Associate Professor, ECED.

The matter presented in this thesis has not been submitted in any other University/Institute for the award of my degree.

Sandeep Kumar

Date: 30/6/2011

Sandeep Kumar

Roll. No. 600961018

It is certified that the above statement made by the student is correct to the best of my knowledge and belief.

30/6/2011

Dr. Sanjay Sharma

Associate Professor

ECED, Thapar University

Counter signed by:

Dr. A. K. Chatterjee

Professor & Head

ECED, Thapar University

Patiala-147004

Dr. S. K. Mohapatra

Dean of Academic Affairs

Thapar University

Patiala-147004

ACKNOWLEDGEMENTS

First of all I would like to thank the Almighty, who has always guided me to work on the right path of the life. I am very thankful to **Dr. Sanjay Sharma, Associate Professor,** Electronics and Communication Engineering Department, Thapar University, Patiala, under whose guidance I had the privilege to complete this thesis. I wish to express my deep gratitude towards him for providing individual guidance and support throughout the thesis work. This work would not have been possible without the encouragement and able guidance of my supervisor **Dr. Sanjay Sharma.** His enthusiasm and optimism made this experience both rewarding and enjoyable. His feedback and editorial comments were also valuable for writing this thesis.

I convey my sincere thanks to **HEAD OF THE DEPARTMENT, Dr. A. K. Chatterjee** as well as **PG Coordinator, Dr. Alpana Agrawal, Assistant Professor,** Electronics and Communication Engineering Department, entire faculty and staff of Electronics and Communication Engineering Department for their encouragement and cooperation.

I am deeply indebted to my parents for their inspiration and ever encouraging moral support, which enabled me to pursue my studies.

My greatest thanks are to all who wished me success. I do not find enough words with which I can express my feelings of thanks to my dear friends for their help, inspiration and moral support which went a long way in successful competition of the present study.

Sandeep Kumar

Sandeep Kumar

ABSTRACT

A lot of hospitals handle their medical image data with computers. The use of computers and a network makes it possible to distribute the image data among the staff efficiently. X-Ray and CT produce sequence of images. The amount of data produced by these techniques is vast and this might be a problem when sending the data over a network. To overcome this problem image compression has been introduced in the field of medical. Medical image compression plays a key role as hospitals. Image compression will allow reducing the file sizes on their storage requirements while maintaining relevant diagnostic information. There have been numerous compression research studies, examining the use of compression as applied to medical images. To achieve higher degree of compression we have to choose ISPIHT and ROI compression technique. This thesis will propose an approach to improve the performance of medical image compression while satisfying medical team who need to use it. There are several types of image compressions available but in case of biomedical images the loss of diagonasability of the image is not tolerable and hence to achieve higher degree of compression without any significant loss in the diagonasability of the image.

This thesis describes the hardware design flow of lifting based Forward Discrete Wavelet Transform (FDWT) processor for ISPIHT and ROI. An effective DWT algorithm has been performed on input image file to get the decomposed image coefficients. The Lifting Scheme reduces the number of operations execution steps to almost one-half of those needed with a conventional convolution approach. The DWT modules were simulated using FPGA design tools. The final design was verified with Matlab image processing tools. Comparison of simulation results Matlab was done to verify the proper functionality of the developed module. The motivation in designing the hardware modules of the DWT was to reduce its complexity, enhance its performance and to make it suitable development on a reconfigurable FPGA based platform for VLSI implementation.

Distortion was evaluated for all images and compression rates by the Peak Signal-to-Noise Ratio (PSNR). For all images, PSNR and BPP performed substantially better than the

traditional SPIHT and a difference in performance was found between SPIHT and ISPIHT and ROI. A comparison applying SPIHT and the ISPIHT to the same set of images and obtaining similar implementation as region-based methods. For digital images, region-based compression methods represent an improvement in compression efficiency from full-image methods, also providing the possibility of encoding multiple regions of interest (ROI) independently.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ABBREVIATIONS

DICOM	Digital Imaging and Communications in Medicine
JPEG	Joint Photographic Experts Group
SPIHT	Set Partioning in Hierarchical Trees
ISPIHT	Improved Set Partioning in Hierarchical Trees
ROI	Region of Interest
CT	Computed Tomography
DCT	Discrete Cosine Transform
DWT	Discrete Wavelet Transform
WT	Wavelet Transform
LIS	List of Insignificant Sets
LIP	List of Insignificant Pixels
LSP	List of Significant Pixels
PSNR	Peak Signal to Noise Ratio
MSE	Mean Squared Error
US	Ultrasound
PROI	Primary Region of Interest
SROI	Secondary Region of Interest
FPGA	Field Programme Gate Array

Chapter 1

Introduction

Medical science grows very fast and hence each hospital needs to store high volume of data about the patients. And medical images are one of the most important data about patients. As a result hospitals have a high volume of images with them and require a huge hard disk space and transmission bandwidth to store these images. Most of the time transmission bandwidth is not sufficient into storing all the image data. Image compression is the process of encoding information using fewer bits (or other information-bearing units) than an un-encoded representation would use through use of specific encoding schemes. Compression is useful because it helps to reduce the consumption of expensive resources, such as hard disk space or transmission bandwidth (computing). On the downside, compressed data must be decompressed, and this extra processing may be detrimental to some applications. For instance, a compression scheme for image may require expensive hardware for the image to be decompressed fast enough to be viewed as its being decompressed (the option of decompressing the image in full before watching it may be inconvenient, and requires storage space for the decompressed image). The design of data compression schemes therefore involves trade-offs among various factors, including the degree of compression, the amount of distortion introduced (if using a lossy compression scheme), and the computational resources required to compress and uncompress the data [1][2]. Data compression is the process of converting data files into smaller ones for efficiency of storage and transmission. Each compression algorithm has its corresponding decompression algorithm that, given the compressed file, should reproduce the original one. Image compression schemes come under two categories: lossless and lossy compression. Lossless compression uses coding techniques to compress the data while retaining all information content. However, in this case the achieved file size reduction is not sufficient for many applications and thus this technique will not be discussed in this paper [2]. Lossy image compression, as its name implies, results in the loss of some information content while the file size reduction can be much more significant than obtained with lossless compression. Since most digital images are intended for human observers, much research is nowadays focused on lossy compression that minimizes visual distortion and possibly obtains visually lossless results. Image compression is the application of Data compression on digital images. Image compression is minimizing the size in bytes of a graphics file without degrading the quality of the image to an

unacceptable level. The reduction in file size allows more images to be stored in a given amount of disk or memory space. It also reduces the time required for images to be sent over the Internet or downloaded from Web pages. . This would imply the need for a compression scheme that would give a very high compression ratio very high compression ratio usually comes with a price. This refers to the quality of the image. Given a particular compression ratio, the quality of the image reconstructed using the SPHIT algorithm make the job more better way even though .the problem comes into picture the issue of energy constraints. While compressing and transmitting an image if the coefficients to be transmitted are of very large magnitude then more resources would be required for transmission. This is taken care of by employing energy efficient compression. But again medical images cannot afford the loss of important details for the sake of meeting battery constraints for telemedicine. This is also taken care of in this work and the regions of diagnostic importance are undisturbed in course of achieving energy efficiency. Another important characteristic, which is often the criterion or even the referred basis of diagnosis in medical images, is the texture of the various regions within the image.

1.1 Basic Steps of Image Compression

There are 2 types of image compression: lossless compression (reversible) and lossy compression (irreversible) Run-length encoded (RLE) and the JPEG lossless compression algorithms are examples of lossless compression [2][3]. In lossy compression, data are discarded during compression and cannot be recovered. Lossy compression achieves much greater compression than does lossless technique. Wavelet and higher-level JPEG are examples of lossy compression. JPEG 2000 is a progressive lossless-to-lossy compression algorithm. JPEG handles only still images, but there is a related standard called MPEG for motion pictures.

- **Compression Algorithms:** There are 3 basic steps:

1. **Transformation**: The discrete wavelet transform cuts the image into blocks of 64 pixels (8 × 8) and processes each block independently, shifting and simplifying the colours so that there is less information to encode.
2. **Quantization**: The values in each block are then divided by a quantization coefficient. This is the compression step where information loss occurs. Pixels are changed only in relation to the other pixels within their block.

3. **Encoding**: The reduced coefficients are then encoded, usually with Huffman coding (entropy encoding that finds the optimal system of encoding based on the relative frequency of each character).With high ratio compression.

1.2 History

In 1949 Claude Shannon and Robert Fano devised a systematic way to assign code words based on probabilities of blocks. An optimal method for doing this was then found by David Huffman in 1951. Early implementations were typically done in hardware, with specific choices of code words being made as compromises between compression and error correction. In the mid-1970s, the idea emerged of dynamically updating code words for Huffman encoding, based on the actual data encountered. And in the late 1970s, with online storage of text files becoming common, software compression programs began to be developed, almost all based on adaptive Huffman coding. In 1977 Abraham Lempel and Jacob Ziv suggested the basic idea of pointer-based encoding. In the mid-1980s, following work by Terry Welch, the so-called LZW algorithm rapidly became the method of choice for most general-purpose compression systems. It was used in programs such as PKZIP, as well as in hardware devices such as modems. In the late 1980s, digital images became more common, and standards for compressing them emerged. In the early 1990s, lossy compression methods also began to be widely used.

1.3 Advancement Of compression Techniques

Walter B. Richardson, revised the challenges faced as technology moved toward digital mammography, presented a necessarily brief overview of multiresolution analysis, and finally, gave current and future applications of wavelets to several areas of mammography.

Armando Manduca, have developed software modules (both stand-alone and in the biomedical image analysis and display package analyze) that could perform wavelet- based compression on both 2-D and 3-D gray scale images. He presented examples of such compression on a variety of medical images, and comparisons with JPEG and other compression schemes.

Arve Kjoelen et.al, studied the rapid growth in the field of diagnostic imaging has produced several new class of digital images, resulting from computerized tomography, magnetic

resonance imaging, and other imaging modalities. In addition, well-established imaging modalities such as X-rays and ultrasound will increasingly be processed and stored in a digital format. It has been estimated that a 600-bed hospital would need almost 2 terabytes (2,000 gigabytes) of storage per year if all images produced at the hospital were to be stored in a digital format. The need for high performance compression algorithms to reduce storage and transmission costs is evident. The compression techniques described herein were likely to be effective for a far wider range of images than the skin tumor images employed in this research.

Mislav GrgiC et.al, discussed the features of wavelet filters in compression of still images and characteristic that they showed for various image content and size. The aim of this work was to create a palette of functions (filters) for implementation of wavelet in still image processing and to emphasize the advantage of this transformation relating to today's methods. Filters taken in the test are some of the most used: Haar filter (as the basis), orthogonal and Biorthogonal filter. All these filters gave various performances for images of different content. Objective and subjective picture quality characteristics of images coded using wavelet transform with different filters were given. The comparison between JPEG coded picture and the same picture coded with wavelet transform was given. For higher compression ratios it was shown that wavelet transform had better S/N.

Reto Grüter et.al, addressed the problem of progressive lossless image coding, A nonlinear decomposition for progressive lossless compression was presented. The decomposition into subbands was called rank-order polynomial decomposition (ROPD) according to the polynomial prediction models used. The decomposition method presented here was a further development and generalization of the morphological subband decomposition (MSD) introduced earlier by the same research group. It was shown that ROPD provides similar or slightly better results than the compared coding schemes such as the codec based on set partitioning in hierarchical trees (SPIHT). The proposed lossless compression scheme had the functionality of having a completely embedded bit stream, which allowed for data browsing. It was shown that the ROPD had a better lossless rate than the MSD but it had also a much better browsing quality when only a part of the bit stream is decompressed. Finally, the possibility of hybrid lossy/lossless compression was presented using ultrasound images. As with other compression algorithms, considerable gain could be obtained if only the regions of interest are compressed lossless.

Wael Badawy et.al, found that with the recent explosion of the Internet, the implementation of technologies such as telemedicine, video conferencing, and wireless data communication have been constrained due to the Internet's finite bandwidth. With the limited technology at hand, techniques were needed to compress a large amount of data into a feasible size before transmission. Data compression had even a greater importance in many applications that involved storage of large data sets, such as magnetic resonance imaging, digital television, and seismic data collection. There were number proposed compression techniques in the literature, but none had unique properties of subband coding algorithms. One such technique presented here was the discrete wavelet transform (DWT), which was one of the most efficient compression algorithms because of its perfect reconstruction property .

Karthik Krishnan et.al, studied that the goals of telemedicine was to enable remote visualization and browsing of medical volumes. There was a need to employ scalable compression schemes and efficient client-server models to obtain interactivity and an enhanced viewing experience. First, they presented a scheme that used JPEG2000 and JPIP (JPEG2000 Interactive Protocol) to transmit data in a multi-resolution and progressive fashion. JPEG2000 for remote volume visualization and volume browsing applications. The resulting system was ideally suited for client-server applications with the server maintaining the compressed volume data, to be browsed by a client with a low bandwidth constraint.

Charalampos Doukas et.al, studied that Medical imaging had a great impact on medicine, especially in the fields of diagnosis and surgical planning. However, imaging devices continue to generate large amounts of data per patient, which require long-term storage and efficient transmission. Current compression schemes produce high compression rates if loss of quality is affordable. However, in most cases physicians may not afford any deficiency in diagnostically important regions of images; called regions of interest (ROIs). An approach that brings a high compression rate with good quality in the ROI was thus necessary. The general theme was to preserve quality in diagnostically critical regions while allowing lossy encoding of the other regions. The aim of the research focused on ROI coding is to allow the use of multiple and arbitrarily shaped ROIs within images, with arbitrary weights describing the degree of importance for each ROI including the background (i.e., image regions not belonging to ROI) so that the latter regions may be represented by different quality levels. In this context, this article provided an overview of state-of the- art ROI coding techniques

applied on medical images. These techniques are classified according to the image type they apply to; thus the first class included ROI coding schemes developed for two-dimensional (2-D) still medical images whereas the second class consists of ROI coding in the case of volumetric images. In the third class, a prototype ROI encoder for compression of angiogram video sequences is presented.

In 2008 Ultrasound, computed tomography (CT), magnetic resonance imaging (MRI) medical imaging produce human body pictures in digital form. These medical applications have already been integrated into mobile devices and are being used by medical personnel in treatment centers, for retrieving and examining patient data and medical images. Storage and transmission are key issues in such platforms, due to the significant image file sizes. Wavelet transform has been considered to be a highly efficient technique of image compression resulting in both lossless and lossy compression of images with great accuracy, enabling its use on medical images. On the other hand, in some areas in medicine, it may be sufficient to maintain high image quality only in the region of interest i.e. in diagnostically important regions. This paper proposes a framework for ROI based compression of medical images using wavelet based compression techniques (i.e. JPEG2000 and SPIHT). Results are analyzed by conducting the experiments on a number of medical images by taking different region of interests. The performance is evaluated using various image quality metrics like PSNR, MSE.

In 2009, Dr.R.Sudhakar, Advanced medical imaging requires storage of large quantities of digitized clinical data [22]. Due to the constrained bandwidth and storage capacity, a medical image must be compressed before transmission and storage. However, the compression will reduce the image fidelity, especially when the images are compressed at lower bit rates. The reconstructed images suffer from blocking artefacts and the image quality will be severely degraded under the circumstance of high compression ratios. Medical imaging poses the great challenge of having compression algorithms that reduce the loss of fidelity as much as possible so as not to contribute to diagnostic errors and yet have high compression rates for reduced storage and transmission time. To meet this challenge several hybrid compression schemes exclusively for medical images are developed in the recent years. This paper presents overview of various compression techniques based on DCT, DWT and ROI.

In 2009 the proposed algorithm presents an application of SPIHT algorithm to color volumetric dicom medical images using wavelet decomposition [7]. The wavelet decomposition is accomplished with biorthogonal 9/7 filters and 5/3 filters. SPIHT is the modern-day benchmark for three dimensional image compressions. The three-dimensional coding is based on the observation that the sequences of images are contiguous in the temporal axis and there is no motion between slices. Therefore, the discrete wavelet transform can fully exploit the inter-slices correlations. The set partitioning techniques involve a progressive coding of the wavelet coefficients. The SPIHT is implemented and the Rate-distortion (Peak Signal-to-Noise Ratio (PSNR) vs. bit rate) performances are presented for volumetric medical datasets by using biorthogonal 9/7. The results are compared with the previous results of JPEG 2000 standards. Results show that SPIHT method exploits the color space relationships as well as maintaining the full embeddedness required by color image sequences compression and gives better performance in terms of the PSNR and compression ratio than the JPEG 2000.

In 2010 Most of the commercial medical image viewers do not provide scalability in image compression and/or encoding/decoding of region of interest (ROI) [27]. This paper discusses a medical application that contains a viewer for digital imaging and communications in medicine (DICOM) images as a core module. The proposed application enables scalable wavelet-based compression, retrieval, and decompression of DICOM medical images and also supports ROI coding/decoding. Furthermore, the presented application is appropriate for use by mobile devices activated in a heterogeneous network. The methodology involves extracting a given DICOM image into two segments, compressing the region of interest with a lossless, quality sustaining compression scheme like JPEG2000, compressing the non-important regions (background, et al.,) with an algorithm that has a very high compression ratio and that does not focus on quality (SPIHT). With this type of the compression work, energy efficiency is achieved and after respective reconstructions, the outputs are integrated and combined with the output from a texture based edge detector. Thus the required targets are attained and texture information is preserved.

In 2010 an **Improved SPIHT** algorithm based on double significant criteria according to define relation between a threshold value and a boundary rate-distortion slope [2], The significant coefficient and trees has been chosen. The selected significant coefficient and trees are quantized.

Yumnam Kirani Singh Proposed a new sub band coding scheme entitled **ISPIHT** (Improved SPIHT). It is simpler in its coding approach yet it is more efficient in time and memory keeping the performance of SPIHT preserved [4]. It requires less no of compression operations during the coding. The memory requirement for ISPIHT is about two times less than SPIHT.

Yin-hua Wu, Long-xu Jin studied that the current stringent need to the real-time compression algorithm of the high-speed and high-resolution image, such as remote sensing or medical image and so on, in this paper, No List SPIHT (NLS) algorithm has been improved, and a fast parallel SPIHT algorithm is proposed, which is suitable to implement with FPGA [5]. It can deal with all bit-planes simultaneously, and process in the speed of 4pixels/period, so the encoding time is only relative to the image resolution. The experimental results show that, the processing capacity can achieve 200MPixels/s, when the input clock is 50MHz, the system of this paper need 2.29ms to complete lossless compression of a 512×512×8bit image, and only requires 1.31ms in the optimal state. The improved algorithm keeps the high SNR unchanged, increases the speed greatly and reduces the size of the needed storage space. It can implement lossless or lossy compression, and the compression ratio can be controlled. It could be widely used in the field of the high-speed and high-resolution image compression.

Chapter 2

Wavelet Transforms

INTRODUCTION TO WAVELETS AND WAVELET TRANSFORMS

2.1 Wavelet Analysis

Wavelet analysis represents the next logical step: a windowing technique with variable-sized regions [5]. Wavelet analysis allows the use of long time intervals where more precise low-frequency information is required and shorter regions where high-frequency information.

Fig 2.1 Wavelet Analysis

Here's what this looks like in contrast with the time-based, frequency-based, and STFT views of a signal:

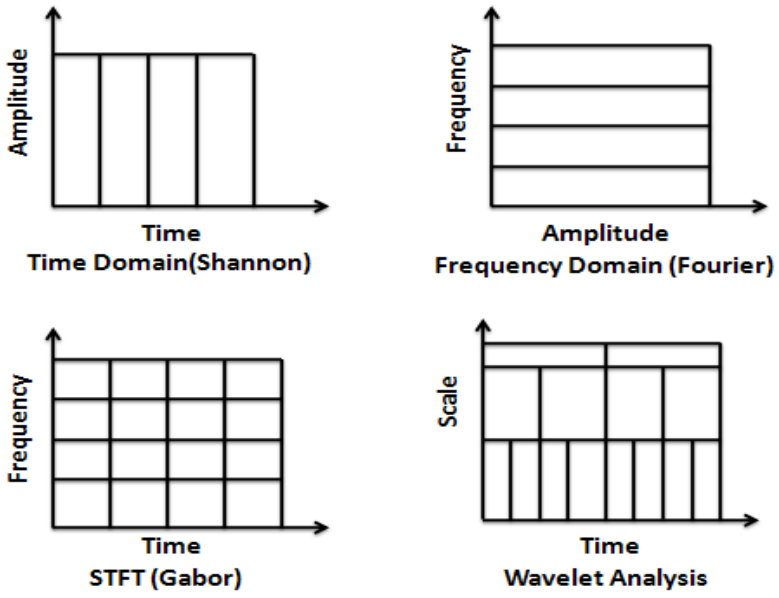


Fig 2.2: Time-based, frequency-based, and STFT views of a signal

You may have noticed that wavelet analysis does not use a time-frequency region, but rather a time-scale region.

2.2 WAVELET

Wavelet means a wavelet is a waveform of effectively limited duration that has an average value of zero [5][6]. Compare wavelets with sine waves, which are the basis of Fourier analysis. 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 symmetric.

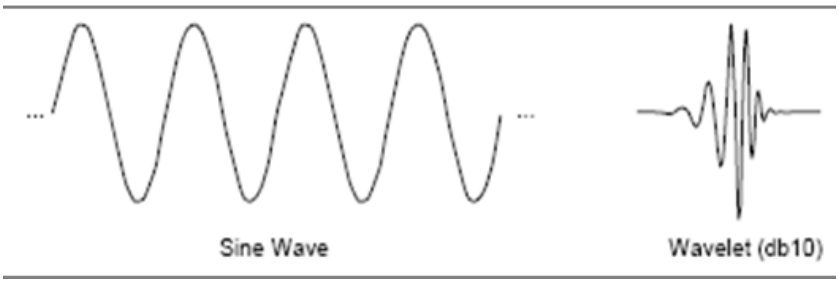


Fig 2.3: Sinusoidal wave

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

2.3 Purpose of Wavelet Analysis

One major advantage afforded by wavelets is the ability to perform local analysis, that is, to analyze a localized area of a larger signal [6][19]. Consider a sinusoidal signal with a small discontinuity one so tiny as to be barely visible. Such a signal easily could be generated in the real world, perhaps by a power fluctuation or a noisy switch. However, a plot of wavelet coefficients clearly shows the exact location in time of the discontinuity.

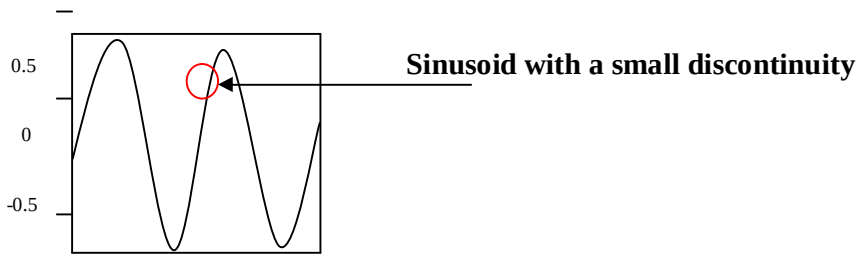


Fig 2.4 Sinusoidal Signal

2.4 Wavelet Transform

When the signal in time for its frequency content is analyzed, Unlike Fourier analysis, in which signals using sines and cosines are analyzed, wavelet functions is used.

- **The Continuous Wavelet Transform**

  Mathematically, the process of Fourier analysis is represented by the Fourier transform:

$$F(\omega) = \int_{-\infty}^{\infty} f(t) e^{-j\omega t} dt$$

Which is the sum over all time of the signal f(t) multiplied by a complex exponential. (Recall that a complex exponential can be broken down into real and imaginary sinusoidal components) [20] The results of the transform are the Fourier coefficients F(w), which when multiplied by a sinusoid of frequency w yields the constituent sinusoidal components of the original signal. Graphically, the process looks like:

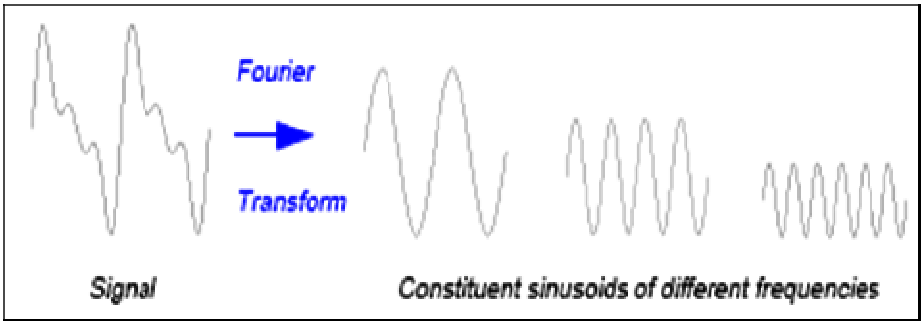


Fig 2.5 Continuous Wavelets of different frequencies

Similarly, the continuous wavelet transform (CWT) is defined as the sum over all time of signal multiplied by scaled, shifted versions of the wavelet function.

$$C(Scale, position) = \int_{-\infty}^{\infty} f(t) \psi(scale, position, t) dt$$

The result of the CWT is a series many wavelet coefficients **C**, which are a function of scale and position**.** Multiplying each coefficient by the appropriately scaled and shifted wavelet yields the constituent wavelets of the original signal:

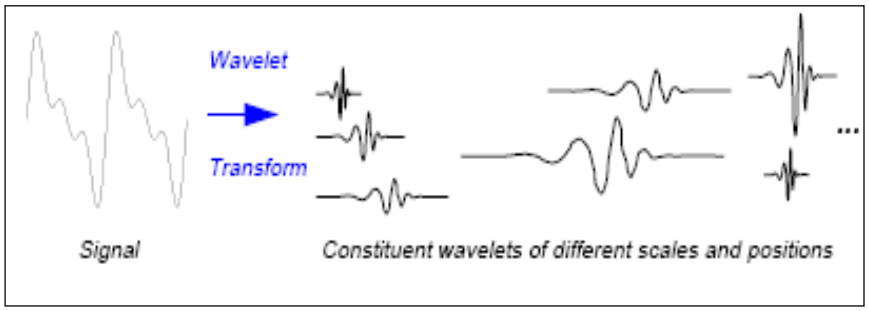


Fig 2.6 Continuous Wavelets of different scales and positions

The wavelet transform involves projecting a signal onto a complete set of translated and dilated versions of a mother wavelet Ψ(t). The strict definition of a mother wavelet will be dealt with later so that the form of the wavelet transform can be examined first. For now, assume the loose requirement that Ψ(t) has compact temporal and spectral support (limited by the uncertainty principle of course), upon which set of basis functions can be defined. The basis set of wavelets is generated from the mother or basic wavelet is defined as

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right) \quad ; \text{a, b} \in \mathrm{R}^1 \text{ and a>0}$$

The variable 'a' (inverse of frequency) reflects the scale (width) of a particular basis function such that its large value gives low frequencies and small value gives high frequencies. The variable 'b' specifies its translation along x-axis in time. The term $1/\sqrt{a}$ is used for normalization. The 1-D wavelet transform is given by:

$$W_f(a,b) = \int_{-\infty}^{\infty} x(t)\psi_{a,b}(t)dt$$

The inverse 1-D wavelet transform is given by:

$$x(t) = \frac{1}{C}\int_0^{\infty}\int_{-\infty}^{\infty} W_f(a,b)\psi_{a,b}(t)db\frac{da}{a^2}$$

Where $C = \int_{-\infty}^{\infty} \frac{|\psi\omega)|^2}{\omega} d\omega < \infty$

X (t) is the Fourier transform of the mother wavelet Ψ(t). *C* is required to be finite, which leads to one of the required properties of a mother wavelet. Since *C* must be finite, then x (t) =0 to avoid a singularity in the integral, and thus the x(t) must have zero mean. This condition can be stated as

$$\int_{-\infty}^{\infty} \psi(t)dt = 0$$

and known as the admissibility condition. The other main requirement is that the mother wavelet must have finite energy:

$$\int_{-\infty}^{\infty} |\psi(t)|^2 dt < \infty$$

A mother wavelet and its scaled versions are depicted in figure 2.10 indicating the effect of scaling.

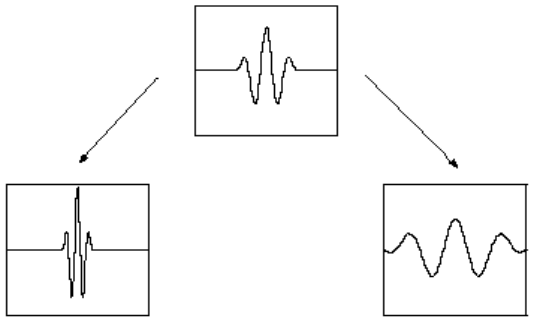


Fig 2.7 Mother wavelet and its scaled versions

Unlike the STFT which has a constant resolution at all times and frequencies, the WT has a good time and poor frequency resolution at high frequencies, and good frequency and poor time resolution at low frequencies.

2.5 Reasons for preferring Wavelet

The compression in wavelet domain is preferred, because it has many advantages:

a) Wavelet-based compression provides multi-resolution hierarchical characteristics. Hence an image can be compressed at different levels of resolution and can be sequentially processed from low resolution to high resolution [7][20][22].

b) High robustness to common signal processing.

c) Real time signals are both time-limited (or space limited in the case of images) and band-limited. Time-limited signals can be efficiently represented by a basis of block functions (Dirac delta functions for infinitesimal small blocks). But block functions are not band-limited. Band limited signals on the other hand can be efficiently represented by a Fourier basis. But sines and cosines are not time-limited. Wavelets are localized in both time (space) and frequency (scale) domains. Hence it is easy to capture local features in a signal.

d) Another advantage of a wavelet basis is that it supports multi resolution. Consider the windowed Fourier transform. The effect of the window is to localize the signal being analyzed. Because a single window is used for all frequencies, the resolution of the analysis is same at all frequencies. To capture signal discontinuities (and spikes), one needs shorter windows, or shorter basis functions. At the same time, to analyze low frequency signal components, one needs longer basis functions. With wavelet based decomposition, the window sizes vary. Thus it allows analyzing the signal at different resolution levels.

2.6 Classification of Wavelets

The wavelets can be classify into two classes: (a) orthogonal and (b) biorthogonal. Based on the application, either of them can be used.

- **Features of orthogonal wavelet filter banks** The coefficients of orthogonal filters are real numbers. The filters are of the same length and are not symmetric. The low pass filter, G0 and the high pass filter, H0 are related to each other by $H0(z) = z^{-N} G0(-z^{-1})$. The two filters are alternated flip of each other. The alternating flip automatically gives double-shift orthogonality between the low pass and high pass filters, i.e., the scalar product of the filters, for a shift by two is zero. i.e., $\Sigma G[k] H[k-2l] = 0$, where $k,l \in Z$. Filters that satisfy equation are known as Conjugate Mirror Filters (CMF) [27]. Perfect reconstruction is possible with alternating flip. Also, for perfect reconstruction, the synthesis filters are identical to the analysis filters except for a time reversal. Orthogonal filters offer a high number of vanishing moments. This property is useful in many signal and image processing applications. They have regular structure which leads to easy implementation and scalable architecture.

- **Features of biorthogonal wavelet filter banks** In the case of the biorthogonal wavelet filters, the low pass and the high pass filters do not have the same length. The low pass filter is always symmetric, while the high pass filter could be either symmetric or anti-symmetric. The coefficients of the filters are either real numbers or integers. For perfect reconstruction, biorthogonal filter bank has all odd length or all even length filters. The two analysis filters can be symmetric with odd length or one symmetric and the other anti symmetric with even length. Also, the two sets of analysis and synthesis filters must be dual. The linear phase biorthogonal filters are the most popular filters for data compression applications.

2.7 Property of Wavelet

Scaling and Shifting

Scaling a wavelet simply means stretching (or compressing) it. The effect of the scaling factor is very easy to see:

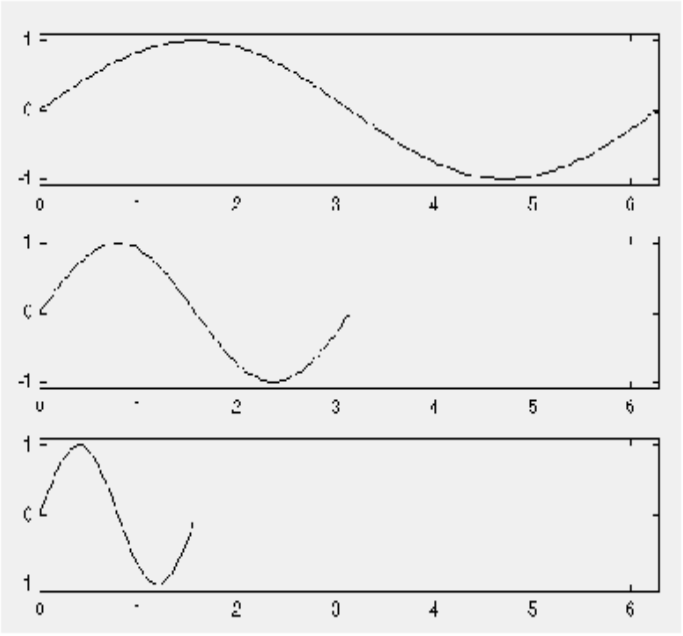
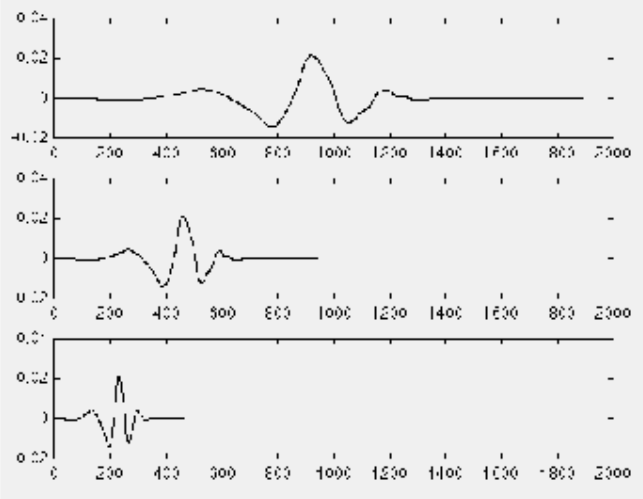


Fig 2.8: General scaling

The scale factor works exactly the same with wavelets. The smaller the scale factor, the more "compressed" the wavelet.



$$f(t) = \psi(t) \quad ; \quad a = 1$$

$$f(t) = \psi(2t) \; ; \quad a = \frac{1}{2}$$

$$f(t) = \psi(4t) \; ; \quad a = \frac{1}{4}$$

Fig 2.9: Scaling in wavelets

It is clear from the diagram that, for a sinusoid $\sin(wt)$, the scale factor a is related (inversely) to the radian frequency w. Similarly, with wavelet analysis, the scale is related to the frequency of the signal. Shifting a wavelet simply means delaying (or hastening) its onset. Mathematically, delaying a function f(t) by k is represented by f(t-k).

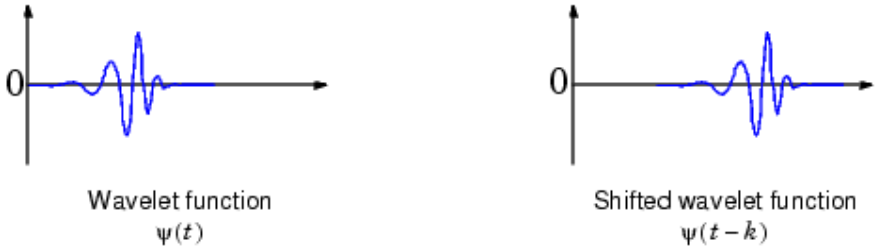


Fig 2.10: Shifting in wavelets

Various other properties of wavelet transforms is described below:

1) Regularity
2) The window for a function is the smallest space-set (or time-set) outside which function is identically zero.
3) The order of the polynomial that can be approximated is determined by number of vanishing moments of wavelets and is useful for compression purposes.
4) The symmetry of the filters is given by wavelet symmetry. It helps to avoid de phasing in image processing. The Haar wavelet is the only symmetric wavelet among orthogonal. For biorthogonal wavelets both wavelet functions and scaling functions that are either symmetric or antisymmetric can be synthesized.

5) Filter length: Shorter synthesis basis functions are desired for minimizing distortion that affects the subjective quality of the image [22]. Longer filters (that correspond to longer basis functions) are responsible for ringing noise in the reconstructed image at low bit rates.

2.8 Architecture of Wavelet

Wavelet compression involves a way analyzing an uncompressed image in a recursive fashion, resulting in a series of higher resolution images, each "adding to" the information content in lower resolution images. The primary steps in wavelet compression are performing a discrete wavelet Transformation (DWT), quantization of the wavelet-space image sub bands, and then encoding these sub bands. Wavelet images by and of themselves are not compressed images; rather it is quantization and encoding stages that do the image compression and to store the compressed image. Wavelet compression inherently results in a set of multi-resolution images; it is well suited to working with large imagery which needs to be selectively viewed at different resolution, as only the levels containing the required level of detail need to be decompressed. The following diagram shows wavelet based compression.

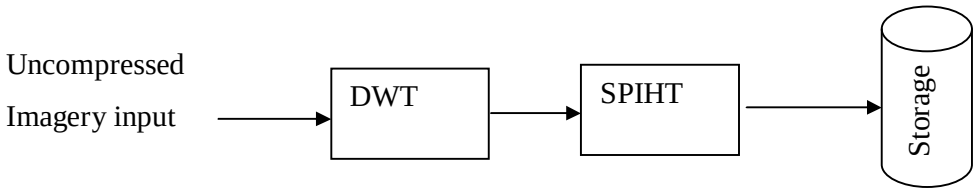


Fig 2.11: Wavelet based image Compression

2.8.1 Decomposition Process

The image is high and low-pass filtered along the rows. Results of each filter are down-sampled by two. The two sub-signals correspond to the high and low frequency components along the rows, each having a size N by N/2. Each of the sub-signals is then again high and low-pass filtered, but now along the column data and the results are again down-sampled by two.

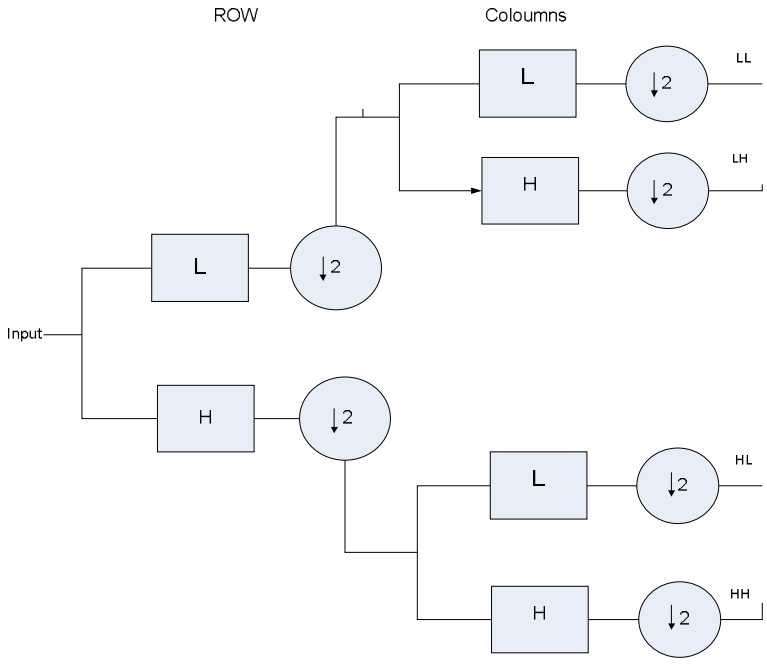


Fig 2.12: One decomposition step of the two dimensional image

Hence, the original data is split into four sub-images each of size N/2 by N/2 and contains information from different frequency components [27]. Figure 3.15 shows the block wise representation of decomposition step.

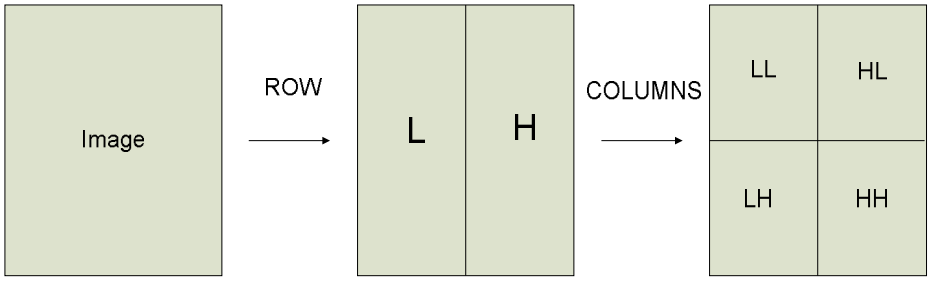


Fig 2.13: One DWT decomposition step

The LL subband obtained by low-pass filtering both the rows and columns, contains a rough description of the image and hence called the approximation subband. The HH Subband, high-pass filtered in both directions, contains the high-frequency components along the diagonals. The HL and LH images result from low-pass filtering in one direction and high-pass filtering in the other direction. LH contains mostly the vertical detail information, which

corresponds to horizontal edges. HL represents the horizontal detail information from the vertical edges. The subbands HL, LH and HH are called the detail subbands since they add the high-frequency detail to the approximation image.

2.8.2 Composition Process

Figure 2.14 corresponds to the composition process. The four sub-images are up-sampled and then filtered with the corresponding inverse filters along the columns [27]. The result of the last step is added together and the original image is retrieved, with no information loss.

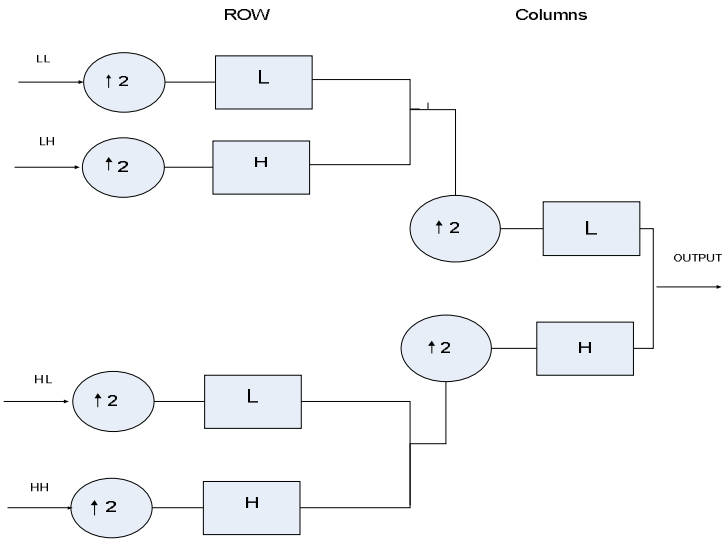


Fig 2.14: One composition step of the four sub images

Chapter 3

Image Compression

3.1 Introduction

Image compression is the process of encoding information using fewer bits (or other information-bearing units) than an encoded representation would use through use of specific encoding schemes. Compression is useful because it helps reduce the consumption of expensive resources, such as hard disk space or transmission bandwidth (computing). On the downside, compressed data must be decompressed, and this extra processing may be detrimental to some applications. For instance, a compression scheme for image may require expensive hardware for the image to be decompressed fast enough to be viewed as it's being decompressed (the option of decompressing the image in full before watching it may be inconvenient, and requires storage space for the decompressed image). The design of data compression schemes therefore involves trade-offs among various factors, including the degree of compression, the amount of distortion introduced (if using a lossy compression scheme), and the computational resources required to compress and uncompress the data.

Image compression is an application of data compression on digital images. Image compression is minimizing the size in bytes of a graphics file without degrading the quality of the image to an unacceptable level. The reduction in file size allows more images to be stored in a given amount of disk or memory space. It also reduces the time required for images to be sent over the Internet or downloaded from Web pages. There are several different ways in which image files can be compressed. For Internet use, the two most common compressed graphic image formats are the JPEG format and SPIHT format.

3.2 Image Compression Algorithms

Image compression can be lossy or lossless. Lossless compression is sometimes preferred for artificial images such as technical drawings, icons or comics. This is because lossy compression methods, especially when used at low bit rates, introduce compression artifacts. Lossless compression methods may also be preferred for high value content, such as medical imagery or image scans made for archival purposes. Lossy methods are especially suitable for

natural images such as photos in applications where minor (sometimes imperceptible) loss of fidelity is acceptable to achieve a substantial reduction in bit rate.

3.2.1 Lossy image compression

A lossy compression method is one where compressing data and then decompressing it retrieves data that may well be different from the original, but is close enough to be useful in some way [23][28]. Lossy compression is most commonly used to compress multimedia data (audio, video, still images), especially in applications such as streaming media and internet telephony. On the other hand lossless compression is required for text and data files, such as bank records, text articles, etc. Lossy compression formats suffer from generation loss: repeatedly compressing and decompressing the file will cause it to progressively lose quality. This is in contrast with lossless data compression. Information-theoretical foundations for lossy data compression are provided by rate-distortion theory. Much like the use of probability in optimal coding theory, rate-distortion theory heavily draws on Bayesian estimation and decision theory in order to model perceptual distortion and even aesthetic judgment.

Various Lossy Compression Methods are:

- Cartesian Perceptual Compression: Also known as CPC
- DjVu
- Fractal compression
- HAM, hardware compression of color information used in Amiga computers
- ICER, used by the Mars Rovers: related to JPEG 2000 in its use of wavelets
- JPEG
- JPEG 2000, JPEG's successor format that uses wavelets.
- JBIG2
- PGF, Progressive Graphics File (lossless or lossy compression) Wavelet compression
- S2TC texture compression for 2-D computer graphics hardware

3.2.2 Lossless Image Compression

Lossless or reversible compression refers to compression techniques in which the reconstructed data exactly matches the original [23]. Lossless compression denotes compression methods, which give quantitative bounds on the nature of the loss that is introduced. Such compression techniques provide the guarantee that no pixel difference

between the original and the compressed image is above a given value. It finds potential applications in remote sensing, medical and space imaging, and multispectral image archiving. In these applications the volume of the data would call for lossy compression for practical storage or transmission. However, the necessity to preserve the validity and precision of data for subsequent reconnaissance, diagnosis operations, forensic analysis, as well as scientific or clinical measurements, often imposes strict constraints on the reconstruction error. In such situations lossless compression becomes a viable solution, as, on the one hand, it provides significantly higher compression gains vis-à-vis lossless algorithms, and on the other hand it provides guaranteed bounds on the nature of loss introduced by compression.

Another way to deal with the lossy-lossless dilemma faced in applications such as medical imaging and remote sensing is to use a successively refinable compression technique that provides a bit stream that leads to a progressive reconstruction of the image. Using wavelets, for example, one can obtain an embedded bit stream from which various levels of rate and distortion can be obtained. In fact with reversible integer wavelets, one gets a progressive reconstruction capability all the way to lossless recovery of the original. Such techniques have been explored for potential use in tele-radiology where a physician typically requests portions of an image at increased quality (including lossless reconstruction) while accepting initial renderings and unimportant portions at lower quality, and thus reducing the overall bandwidth requirements. In fact, the new still image compression standard, JPEG 2000, provides such features in its extended form.

Various Loss-Less Compression Method are:

- Run-length encoding – used as default method in PCX and as one of possible in BMP, TGA, TIFF
- Entropy coding
- Adaptive dictionary algorithms such as LZW – used in GIF and TIFF
- Deflation – used in PNG, MNG and TIFF

The usual steps involved in compressing and decompressing of image are:

Step 1: Specifying the Rate (bits available) and Distortion (tolerable error) parameters for the target image.

Step 2: Dividing the image data into various classes, based on their importance.

Step 3: Dividing the available bit budget among these classes, such that the distortion is a minimum.

Step 4: Quantize each class separately using the bit allocation information derived in step 2.

Step 5: Encode each class separately using an entropy coder and write to the file.

Step 6: Reconstructing the image from the compressed data is usually a faster process than compression. The steps involved are

Step 7: Read in the quantized data from the file, using an entropy decoder (reverse of step 5).

Step 8: Dequantize the data. (Reverse of step 4).

Step 9: Rebuild the image. (Reverse of step 2).

3.3 Types of Image Compression

The various types of image compression methods are described below:

3.3.1 Joint Photographic Experts Group (JPEG)

JPEG stands for Joint Photographic Experts Group, the original name of the Committee that wrote the standard. JPEG is designed for compressing full-color or gray-scale images of natural, real-world scenes [26]. It works well on photographs, naturalistic artwork, and similar material; not so well on lettering, simple cartoons, or line drawings. JPEG handles only still images, but there is a related standard called MPEG for motion pictures. JPEG is "lossy," meaning that the decompressed image isn't quite the same as the one you started with. (There are lossless image compression algorithms, but JPEG achieves much greater compression than is possible with lossless methods.) JPEG is designed to exploit known limitations of the human eye, notably the fact that small color changes are perceived less accurately than small changes in brightness. Thus, JPEG is intended for compressing images that will be looked at by humans. If you plan to machine-analyze your images, the small errors introduced by JPEG may be a problem for you, even if they are invisible to the eye. A useful property of JPEG is that the degree of lossiness can be varied by adjusting compression parameters. This means that the image maker can trade off file size against output image quality. You can make extremely small files if you don't mind poor quality; this is useful for applications such as indexing image archives. Conversely, if you aren't happy with the output quality at the default compression setting, you can jack up the quality until you are satisfied, and accept lesser compression. Another important aspect of JPEG is that decoders can trade off decoding speed against image quality, by using fast but inaccurate

approximations to the required calculations. Some viewers obtain remarkable speedups in this way. (Encoders can also trade accuracy for speed, but there's usually less reason to make such a sacrifice when writing a file).

3.3.2 Set Partioning in Hierarchical Trees (SPIHT)

SPIHT is the wavelet based image compression method. It provides the Highest Image Quality, Progressive image transmission, fully embedded coded file, Simple quantization algorithm, fast coding/decoding, completely adaptive, Lossless compression, Exact bit rate coding and Error protection[6][11]. SPIHT makes use of three lists – the List of Significant Pixels (LSP), List of Insignificant Pixels (LIP) and List of Insignificant Sets (LIS). These are coefficient location lists that contain their coordinates. After the initialization, the algorithm takes two stages for each level of threshold – the sorting pass (in which lists are organized) and the refinement pass (which does the actual progressive coding transmission). The result is in the form of a bit stream. It is capable of recovering the image perfectly (every single bit of it) by coding all bits of the transform. However, the wavelet transform yields perfect reconstruction only if its numbers are stored as infinite imprecision numbers. Peak signal-to-noise ratio (PSNR) is one of the quantitative measure for image quality evaluation which is based on the mean square error (MSE) of the reconstructed image. The MSE for N x M size image is given by:

$$MSE = \frac{1}{MN} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} \left\| I(i, j) - K(i, j) \right\|^2$$

Where *f (i,j)* is the original image data and *f ' (i,j)* is the compressed image value. The formula for PSNR is given by:

$$\text{PSNR} = 10 \log ((255)^2 / \text{MSE})$$

SPIHT CODING ALGORITHM:

Since the order in which the subsets are tested for significance is important in a practical implementation the significance information is stored in three ordered lists called list of

insignificant sets (LIS) list of insignificant pixels (LIP) and list of significant pixels (LSP). In all lists each entry is identified by a coordinate (i, j) which in the LIP and LSP represents individual pixels and in the LIS represents either the set D (I, j) or L (I, j) [13][17]. To differentiate between them it can be concluded that a LIS entry is of type A if it represents D (i,j) and of type B if it represents L(I, j). During the sorting pass the pixels in the LIP-which were insignificant in the previous pass-are tested and those that become significant are moved to the LSP. Similarly, sets are sequentially evaluated following the LIS order, and when a set is found to be significant it is removed from the list and partitioned. The new subsets with more than one element are added back to the LIS, while the single coordinate sets are added to the end of the LIP or the LSP depending whether they are insignificant or significant respectively. The LSP contains the coordinates of the pixels that are visited in the refinement pass. Below the new encoding algorithm in presented.

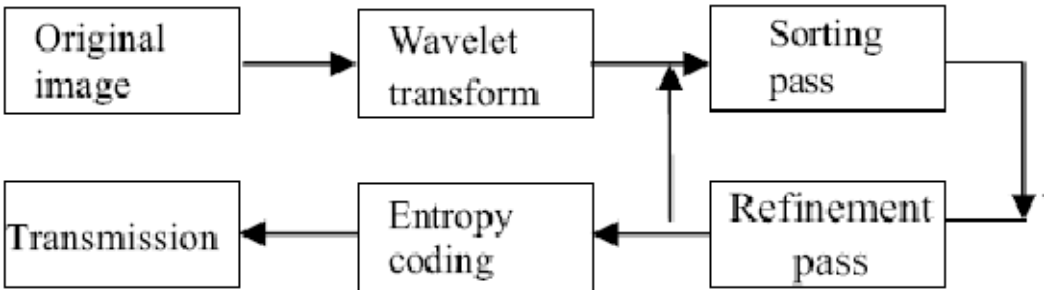


Fig 3.1: Flow Chart of SPIHT

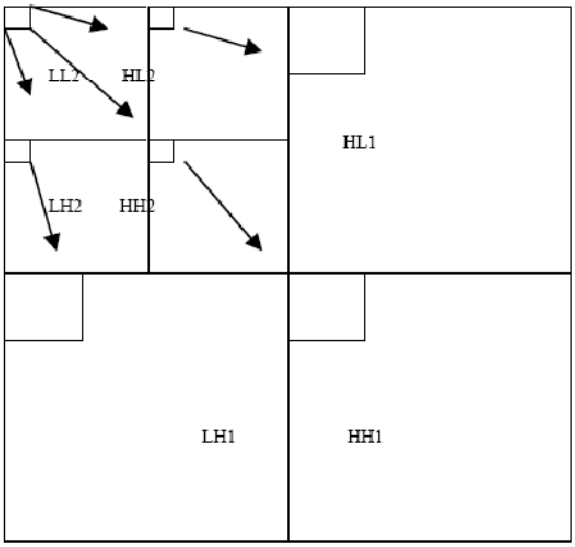


Fig 3.2: Tree Structure of SPIHT

ALGORITHM

1. Initialization: output $n= |\log_2 (\max_{(i, j)} \{c (i, j)\}|$; set the LSP as an empty list, and add the coordinates (i,j) € H to the LIP, and only those with descendants also to the LIS, as type A entries [7].
2. Sorting pass:
   2.1 for each entry (i,j) in the LIP do:
      2.1.1 output Sn (i,j)
      2.1.2 if Sn (i,j) then move (i,j) to the LSP and output the sign of c(i,j)
   2.2 for each entry(i,j) in the LIS do:
      2.2.1 if the entry is of type A then
      - output Sn(D(i,j));
      - if Sn(D(i,j)) then
        for each (k,l) € O(i,j)do:
        output Sn(k,l);
        if Sn(k,l) then add (k,l) to the LSP and output the sign of $c_{k,l;}$
        if Sn (k,l) = 0 then add (k,l) to the end of the LIP;
        if L(i,j)≠0then move (i,j) to the end of the LIS, as an entry of type B and go to Step2.2.2 else, remove entry (i,j) from the LIS;

      2.2.2 if the entry is of type B then
      - Output Sn(L(i,j));
      - if Sn (L(i,j)) = 1 then
        add each (k,l) € O(i,j) to the end of the LIS as an entry of type A;
        remove (i,j) from the LIS.

3. Refinement pass for each entry (i,j) in the LSP, except those included in the last sorting pass (with same n), output the n-th most significant bit of $|c_{i,j}|$;
4. Quantization-step update: decrement n by 1 and go to Step 2

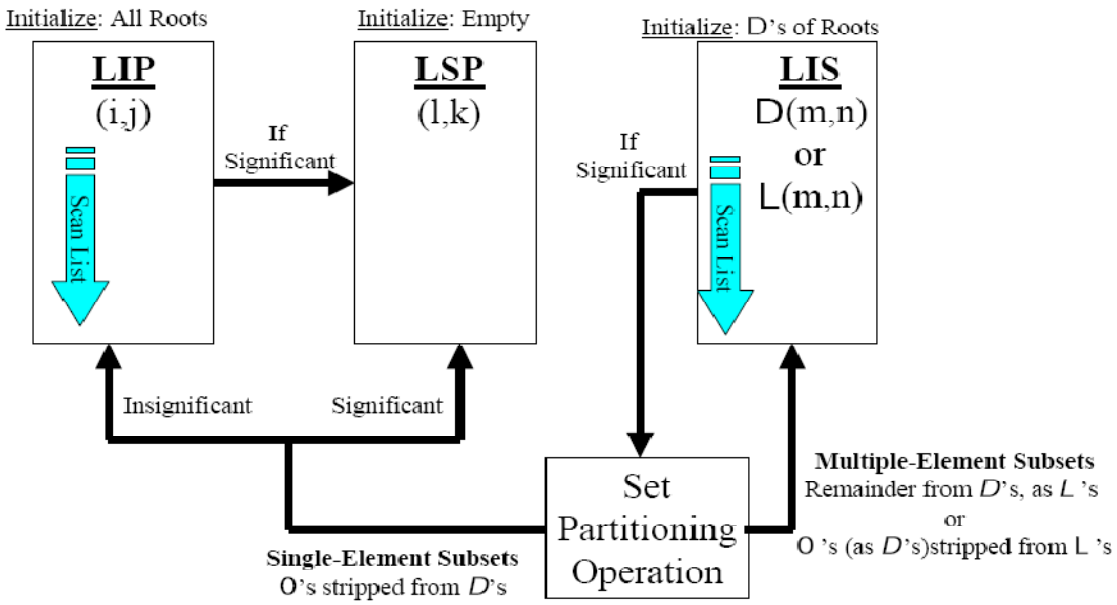


Fig 3.3: SPIHT SORTING PASS

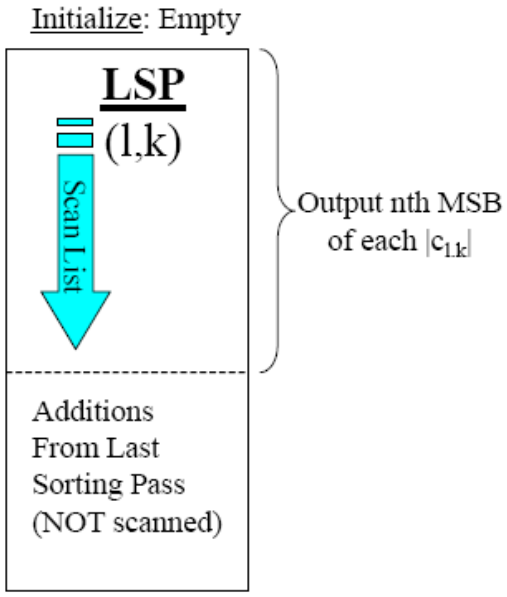
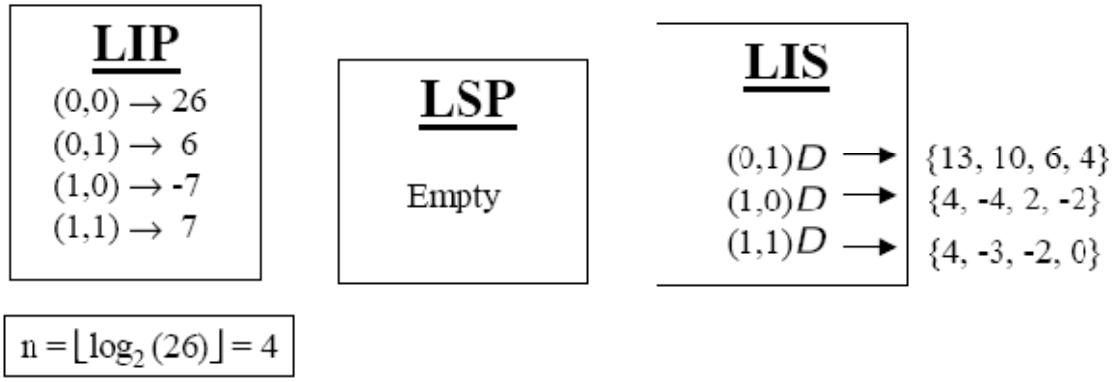


Fig 3.4: SPIHT REFINMENT PASS

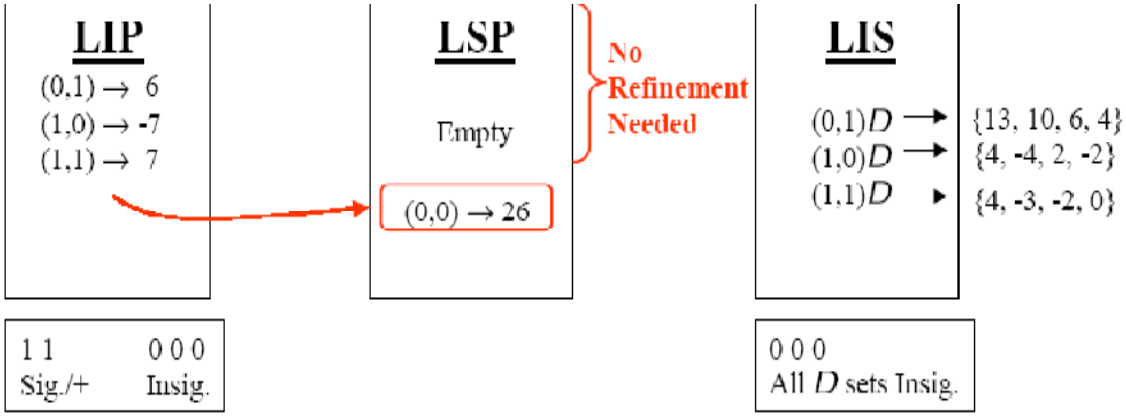
EXAMPLE OF SPIHT:

26	6	13	10
-7	7	6	4
4	-4	4	-3
2	-2	-2	0

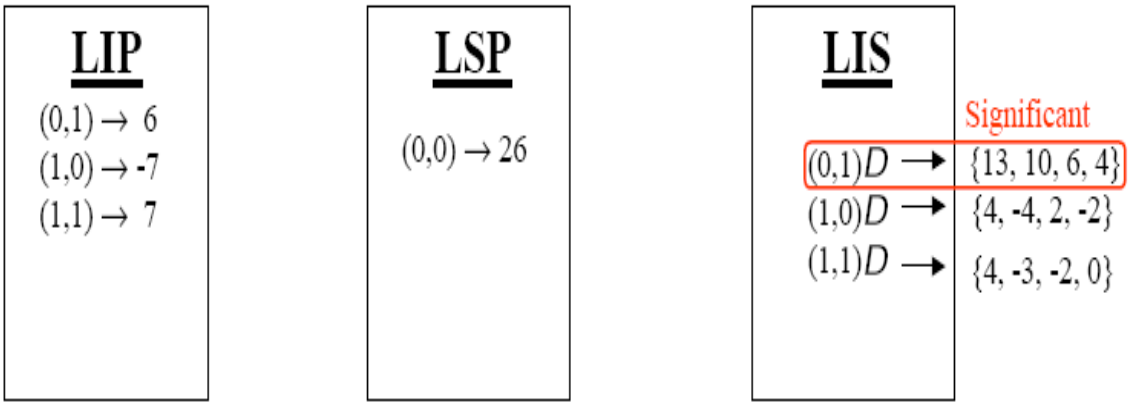
INIALIZATION:



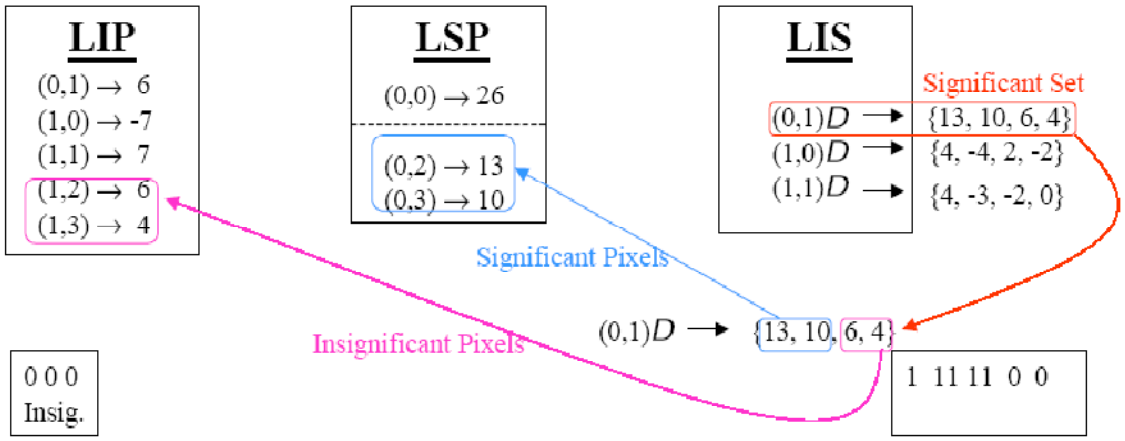
AFTER FIRST SORTING: Threshold=16



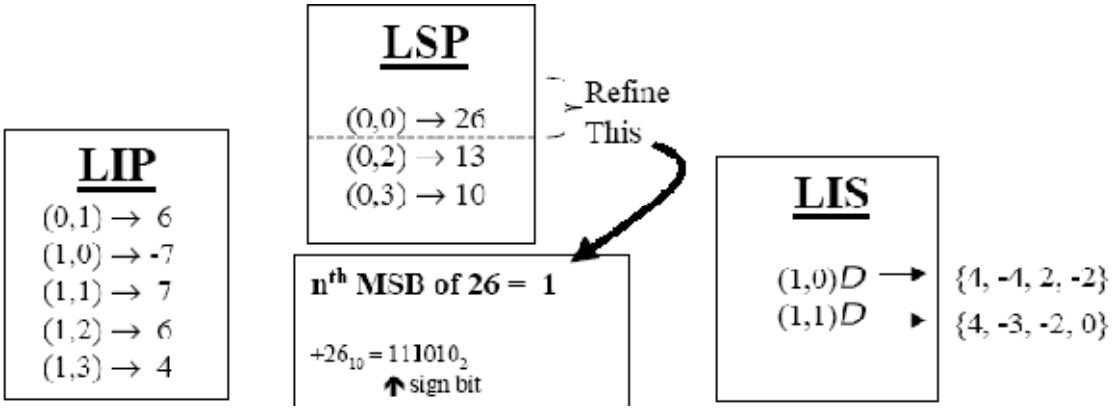
AFTER FIRST REFINMENT:



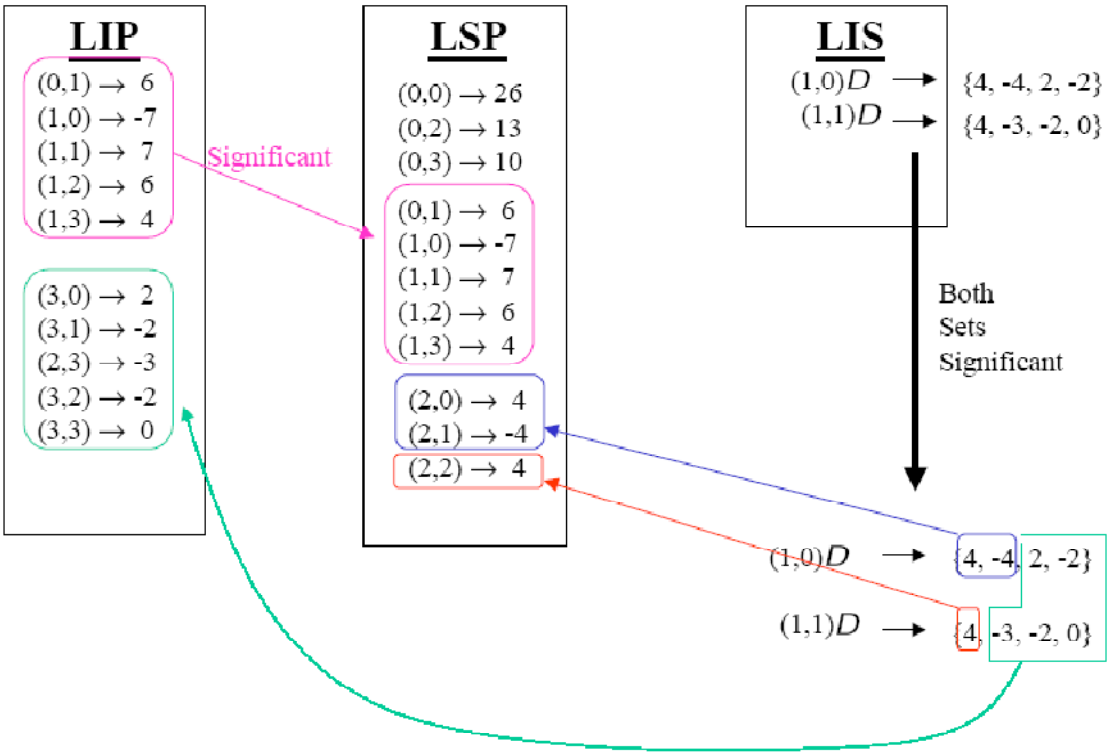
AFTER SECOND SORTING: Threshold=8 , n=3



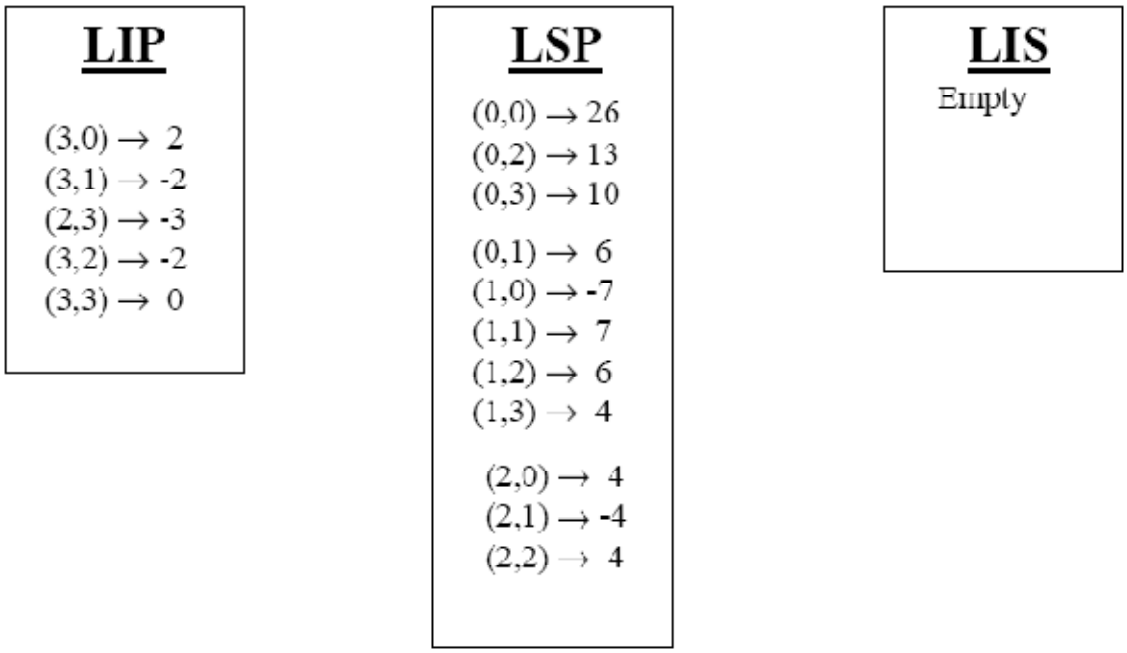
AFTER SECOND REFINMENT:



DURING THIRD SORTING: Threshold=4 , n=2



AFTER THIRD SORTING:



Advantages of SPIHT

The powerful wavelet-based image compression method called Set Partitioning in Hierarchical Trees (SPIHT). The SPIHT method is not a simple extension of traditional methods for image compression, and represents an important advance in the field. The method deserves special attention because it provides the following:

1) Highest Image Quality
2) Progressive image transmission
3) Fully embedded coded file
4) Simple quantization algorithm
5) Fast coding/decoding
6) Completely adaptive
7) Lossless compression
8) Exact bit rate coding
9) Error protection

Each of these properties is discussed below. Note that different compression methods were developed specifically to achieve at least one of those objectives [11]. What makes SPIHT really outstanding is that it yields all those qualities simultaneously**.** So, if in the future you find one method that claims to be superior to SPIHT in one evaluation parameter (like PSNR), remember to see who wins in the remaining criteria.

Image Quality: Extensive research has shown that the images obtained with wavelet-based methods yield very good visual quality [5][18]. At first it was shown that even simple coding methods produced good results when combined with wavelets and is the basis for the most recently JPEG2000 standard. However, SPIHT belongs to the next generation of wavelet encoders, employing more sophisticated coding. In fact, SPIHT exploits the properties of the wavelet-transformed images to increase its efficiency. Many researchers now believe that encoders that use wavelets are superior to those that use DCT or fractals. The SPIHT advantage is even more pronounced in encoding colour images, because the bits are allocated automatically for local optimality among the colour components, unlike other algorithms that encode the colour components separately based on global statistics of the individual components. You will be amazed to see that visually lossless color compression is obtained with some images at compression ratios from 100-200:1.

Progressive Image Transmission: In some systems with progressive image transmission the quality of the displayed images follows the sequence:

(a) weird abstract art;

(b) you begin to believe that it is an image of something;

(c) CGA-like quality;

(d) Lossless recovery.

With very fast links the transition from (a) to (d) can be so fast that you will never notice. With slow links (how "slow" depends on the image size, colors, etc.) the time from one stage to the next grows exponentially, and it may take hours to download a large image. Considering that it may be possible to recover an excellent-quality image using 10-20 times less bits, it is easy to see the inefficiency. Furthermore, the mentioned systems are not efficient even for lossless transmission. The problem is that such widely used schemes employ a very primitive progressive image transmission method. On the other extreme, SPIHT is a state-of-the-art method that *was* designed *for* optimal progressive transmission (and still beats most non-progressive methods!). It does so by producing a fully embedded coded file (see below), in a manner that at any moment the quality of the displayed image is the best available for the number of bits received up to that moment. So, SPIHT can be very useful for applications where the user can quickly inspect the image and decide if it should be really downloaded, or is good enough to be saved, or need refinement.

- **Optimized Embedded Coding:** A strict definition of the embedded coding scheme is: if two files produced by the encoder have size M and N bits, with $M > N$, then the file with size N is *identical* to the first N bits of the file with size M. Let's see how this abstract definition is used in practice. Suppose you need to compress an image for three remote users. Each one have different needs of image reproduction quality, and you find that those qualities can be obtained with the image compressed to at least 8 Kb, 30 Kb, and 80 Kb, respectively. If you use a non-embedded encoder (like JPEG), to save in transmission costs (or time) you must prepare one file for each user. On the other hand, if you use an embedded encoder (like SPIHT) then you can compress the image to a single 80 Kb file, and then send the first 8 Kb of the file to the first user, the first 30 Kb to the second user, and the whole file to the third user. SPIHT *all* three users would get an image quality comparable or superior to the most sophisticated non-embedded encoders available today. SPIHT achieves this feat by optimizing the

embedded coding process and always coding the most important information first. An even more important application is for progressive image transmission, where the user can decide at which point the image quality satisfies his needs, or abort the transmission after a quick inspection, etc.

- **Compression Algorithm:** The following is a comparison of image quality and artifacts at high compression ratios versus JPEG. SPIHT represents a small "revolution" in image compression because it broke the trend to more complex (in both the theoretical and the computational senses) compression schemes. While researchers had been trying to improve previous schemes for image coding using very sophisticated vector quantization, SPIHT achieved superior results using the *simplest* method: uniform scalar quantization. Thus, it is much easier to design fast SPIHT code.

- **Decoding Speed:** The SPIHT process represents a very effective form of entropy-coding. This is shown by the demo programs using two forms of coding: binary-uncoded (extremely simple) and context-based adaptive arithmetic coded (sophisticated). Surprisingly, the difference in compression is small, showing that it is not necessary to use slow methods (and also pay royalties for them!). A fast version using Huffman codes was also successfully tested, but it is not publicly available. A straightforward consequence of the compression simplicity is the greater coding/decoding speed [5]. The SPIHT algorithm is nearly symmetric, i.e., the time to encode is nearly equal to the time to decode. (Complex compression algorithms tend to have encoding times much larger than the decoding times.) Some of our demo programs use floating-point operations extensively, and can be slower in some CPUs (floating points are better when people want to test you programs with strange 16 bpp images). However, this problem can be easily solved: try the lossless version to see an example. Similarly, the use for progressive transmission requires a somewhat more complex and slower algorithm. Some shortcuts can be used if progressive transmission is not necessary. When measuring speed please remember that these demo programs were written for academic studies only, and were not fully optimized as are the commercial versions.

Applications: SPIHT exploits properties that are present in a wide variety of images. It had been successfully tested in natural (portraits, landscape, weddings, etc.) and medical (X-ray, CT, etc) images. Furthermore, its embedded coding process proved to be effective in a broad range of reconstruction qualities. For instance, it can code fair-quality portraits and high-quality medical images equally well (as compared with other methods in the same conditions). SPIHT has also been tested for some less usual purposes, like the compression of elevation maps, scientific data, and others.

- **Lossless Compression:** SPIHT codes the individual bits of the image wavelet transform coefficients following a bit-plane sequence [7][17]. Thus, it is capable of recovering the image perfectly (every single bit of it) by coding all bits of the transform. However, the wavelet transform yields perfect reconstruction only if its numbers are stored as infinite-precision numbers. In practice it is frequently possible to recover the image perfectly using rounding after recovery, but this is not the most efficient approach. For lossless compression an integer multiresolution transformation is proposed, similar to the wavelet transform, which is called S+P transform. It solves the finite-precision problem by carefully truncating the transform coefficients *during* the transformation (instead of after). A codec that uses this transformation to yield efficient progressive transmission up to lossless recovery is among the SPIHT demo programs. A surprising result obtained with this codec is that for lossless compression it is as efficient as the most effective lossless encoders (lossless JPEG is definitely not among them). In other words, the property that SPIHT yields progressive transmission with practically no penalty in compression efficiency applies to lossless compression too. Below are examples of Lossless and lossy (200:1) images decoded from the same file.

- **Rate or Distortion Specification:** Almost all image compression methods developed so far do not have precise rate control. For some methods you specify a target rate, and the program tries to give something that is not too far from what you wanted. For others you specify a "quality factor" and wait to see if the size of the file fits your needs. (If not, just keep trying...) The embedded coding property of SPIHT allows *exact* bit rate control, without any penalty in performance (no bits wasted with padding or whatever). The same property also allows exact mean squared-error

(MSE) distortion control. Even though the MSE is not the best measure of image quality, it is far superior to other criteria used for quality specification.

- **Error Protection:** Errors in the compressed file cause havoc for practically all important image compression methods. This is not exactly related to variable length entropy-coding, but to the necessity of using context generation for efficient compression. For instance, Huffman codes have the ability to quickly recover after an error. However, if it is used to code run-lengths, then that property is useless because all runs after an error would be shifted [6][7][18]. SPIHT is not an exception for this rule. One difference, however, is that due to SPIHT's embedded coding property, it is much easier to design efficient error-resilient schemes. This happens because with embedded coding the information is sorted according to its importance, and the requirement for powerful error correction codes decreases from the beginning to the end of the compressed file. If an error is detected, but not corrected, the decoder can discard the data after that point and still display the image obtained with the bits received before the error. Also, with bit-plane coding the error effects are limited to below the previously coded planes. Another reason is that SPIHT generates two types of data. The first is sorting information, which needs error protection as explained above. The second consists of uncompressed sign and refinement bits, which do not need special protection because they affect only one pixel. While SPIHT can yield gains like 3 dB PSNR over methods like JPEG, its use in noisy channels, combined with error protection as explained above, leads to much larger gains, like 6-12 dB. (Such high coding gains are frequently viewed with skepticism, but they do make sense for combined source-channel coding schemes.)

3.3.3 Improved Set Partioning in Hierarchical Trees (ISPIHT)

ISPIHT is the wavelet based image compression method it provides the Highest Image Quality [1]. The improved SPIHT algorithm mainly makes the following changes. SPIHT codes four coefficients and then shifts to the next four ones. Therefore, views the four coefficients as a block. The maximum of them regarded as the compared threshold will decrease number of comparison, which is relate with the distribution of coefficient matrix. Even more, when the maximum in the block is smaller than the current threshold or equal to it, the block will be coded with only one bit instead of four zeros. Therefore, this proposed method can reduce redundancy to a certain extend. When computing the maximum threshold,

the improved algorithm can initialize the maximum of every block. So, it can obviously reduce number of comparison when scanning and coding zero trees. The coefficients in non-important block will be coded in next scanning process or later, rather than be coded in the present scanning process. This method can implement the coefficients coded earlier to the non-important ones more adequately. Generally, wavelet transform coding for still image using SPIHT [8] algorithm can be modelled as Fig. Firstly, original image matrix goes through wavelet transform. The output wavelet coefficients are then quantized and encoded by SPIHT coder. After that, bit streams are obtained. Figure I. Wavelet transform image coding using SPIHT Traditional SPIHT has the advantages of embedded code stream structure, high compression rate, low complexity and easy to implement [9]. However, for it, there still exist several defects.

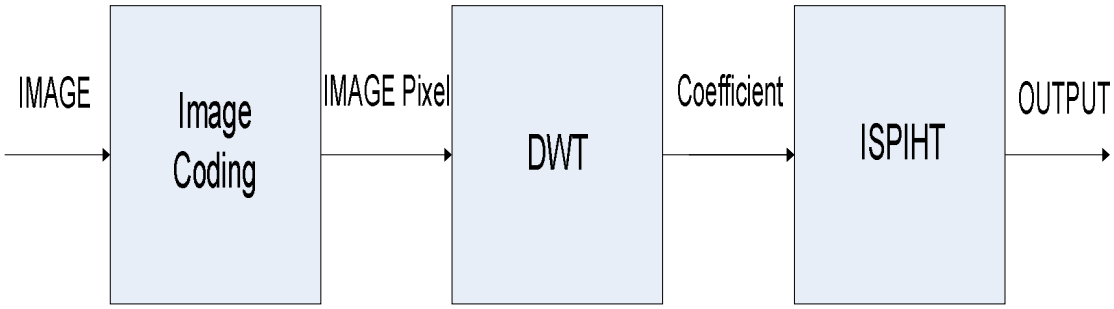


Fig 3.5: Block diagram of ISPIHT

1) When scanning the list of insignificant pixels (LIP), list of insignificant sets (LIS), or list of significant pixels (LSP), the repeated coefficient comparison can increase complexity of the algorithm.
2) The coefficients put into LIP at last scanning procedure which are smaller than the current threshold will result in redundancy.
3) Early coding for non-important coefficients in SPIHT will affect the performance of channel coding, especially unequal error protection (UEP).

Therefore, the improved SPIHT algorithm mainly makes the following changes.

- SPIHT codes four coefficients and then shifts to the next four ones. Therefore, views the four coefficients as a block [1][4]. The maximum of them regarded as the compared threshold will decrease number of comparison, which is relate with the

distribution of coefficient matrix. Even more, when the maximum in the block is smaller than the current threshold or equal to it, the block will be coded with only one bit instead of four zeros. Therefore, this proposed method can reduce redundancy to a certain extend.

- When computing the maximum threshold, the improved algorithm can initialize the maximum of every block. So, it can obviously reduce number of comparison when scanning and coding zero trees.
- The coefficients in non-important block will be coded in next scanning process or later, rather than be coded in the present scanning process [1]. This method can implement the coefficients coded earlier to the non-important ones more adequately. On the basis of above-mentioned ideas for algorithm improvement, an improved algorithm is proposed and briefly describe it in the following paragraphs. In order to comprehend conveniently, symbols are given firstly. B(i,j) which represents a wavelet coefficient block with coordinate (i, j) includes four coefficients (i, j), (i+ 1, j), (i, j+l) and (i+l, j+l), like SPIHT described in detail in and will be divided into its four off springs with coordinates (2i, 2j), (2i+2,2 j), (2i, 2j+2) and (2i+2, 2j+2) . O(i, j): set of coordinates of all off springs of B(i,j). D(i, j): set of coordinates of all descendants of B(i,j) . L(i, j)=D(i, j)-O(i, j). LSP={P(i, j)IP(i, j) E H} and LIS have the same definitions as in. But the set in LIS represents either D(i, j) or L(i, j). To distinguish them, the type D represents D(i, j) and type L for L(i, j). Define list of insignificant block as LlB= {B(i, j)1(i, j) E H} instead of LIP. It stores the first coordinate of a group of 2X2 adjacent pixels which are regarded as a block. H stands for the wavelet coefficient matrix. Our algorithm encodes the sub band pixels by performing initialization and a sequence of sorting pass, refinement pass and quantization-step updating. However, differences of initialization and sorting pass still exist between the improved SPIHT [3] and traditional SPIHT.

4) **Initialization:** LlB={B(O,O), B(0,2), B(2,0), B(2,2)}, LlS={D(0,2), D(2,0), D(2,2)}, T=2n, Cij is wavelet matrix coefficient and LSP is empty. n is expressed in (1).

$$n = \left|\log_2(\max_{(i,j)} |C_{i,j}|)\right|$$

C·l,j· is the matrix coefficient after DWT and (i, j) is the coordinate of Ci,}

5) **Sorting pass:** The sorting pass consists of two tests: the LIB test (LIBT) and LIS test (LIST). The LIBT will code the block or coefficients in blocks, while the LIST

mainly disposes the sets in LIS. In each LlBT, if the maximum value of the coefficient block is smaller than the current threshold, the block is insignificant and ° is the coded bit. Otherwise, 1 will be output and represented the significance of the block. Then, the four coefficients will be respectively compared to the current threshold. When the coefficient has not been put into LSP, if it is insignificant. Otherwise, 10 or 11 represent significant negative sign or significant positive sign, respectively. After that, it will be removed from the block and added to the tail of LSP. While the test is finished, the block will be removed from LIB if all the four coefficients have been put into LSP. Otherwise, the block will be tested again in next LlBT. While in LIST, the set in LIS will be tested and coded according to its type. For type D, if the maximum coefficient in D(i,j) is smaller than the current threshold, the set is insignificant. Otherwise, the significant bit I will be coded and D(i, j) will be divided into its children tree and four blocks with coordinate (m, n) E Q(i, j) rather than four adjacent coefficients. The four blocks will be coded with the style as in LIBT, but the tail of LIB corresponding to their significances. After coding the four blocks, our algorithm will alter D(i,j) to L(i,j) and add L(i,j) to the tail of LIS if D(i,j) has grandson coefficients. Then, set D(i,j) will be removed from LIS. For type L, if the maximum coefficient in L(i, j) is smaller than the current threshold, ° will be output and represented the insignificance of the set . Otherwise, the significant bit 1 will be coded and L(i,j) will be divided into four sets D(m,n), (m, n) E Q(i,) which will be added to the tail of LIS. Then, set L(i,j) will be removed from LIS. After completing LlPT and LlBT tests, the same refinement pass and updating the threshold as in traditional is performed SPIHT. For the improved SPIHT, when the maximum value of a coefficient block put into LIB is small enough, only one bit will used to represent it and the four coefficients of it will not be coded until the current threshold is smaller than the maximum value. Therefore, this algorithm can better avoid repeat coding and early coding for non-important coefficients better. Moreover, this algorithm has the same scanning order and method to determine importance of wavelet coefficients as SPIHT [2][3]. Consequently, it will inherit many advantages of SPIHT.

Algorithm: ISPIHT Coding

Output: Bit stream

Input: Wavelet co-efficient or data matrix to be coded, A, the number of threshold levels, N.

Assign LIP={ A(1,1), A(1,2), A(2,1), A(2,2)}

Assign LIS with VTs for coordinates (1,3), (3,1) and (3,3) as type-0 descendent trees.

Compute Vm, M, Threshold (as described in the Initialization).

Assign Lp1=0;

Comment: Sorting Pass

For I=1 to N

Comment: LIP Testing

For each pixel in the LIP

If a pixel is significant

Send a 1, followed by sign bit.

Delete the pixel form LIP and append its absolute value to LSP.

Else

Send a 0

End **if**

End **For each**

Comment: LIS Testing

For each VT in LIS

If the type of VT is 0

If VT is significant

Send a 1

For each of the four pixels associated with the node of the VT.

If a pixel is significant,

Send a 1 followed by sign bit.

Append the absolute value of the pixel to LSP.

Else

Send a 0

Append the pixel to LIP

End **If**

End **For each**

If VT has more than 1 element

Neglect the first element, change its stype to 1 and append to LIS.

End **If**

Else

Send a 0

End **If**

Else

If VT (of type-1) is significant

Send a 1

Generate VT corresponding to the four top leftmost pixel co-ordinates of the four 2x2 sub-matrices associated with current node.

Delete the VT from the LIS.

Else

Send a 0

End **If**

End **If**

End **For each**

Comment: Refinement Pass

For r=1 to Lp1

If (LSP(r) –Threshold)>=Threshold/2

Send a 1

Else

Send a 0

End **if**

End **For**

Lp1=No. of pixels in the LSP

Threshold=Threshold/2;

End **For**

The decoding algorithm is just the reverse of the coding algorithm. But a difference with coding algorithm is that the LIP and LSP are stored as co-ordinates [1] and the LIS stores only the pixel co-ordinates of the topmost modes of the descendent trees and does not store VTs. Because during the decoding, testing whether a descendent tree is significant or not requires only whether the corresponding bit is 1 or zero, it does not require exhaustive

searching as in the case of coding. In other words decoding remains the same as in SPIHT except the way of representation of the tree structure.

3.4 Terms used in Image Compression

There are various types of terms that are used in calculation of image compression. Some are listed below:

3.4.1 Peak signal to noise ratio

The phrase peak signal-to-noise ratio, often abbreviated PSNR, is an engineering term for the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation [14][18]. Because many signals have a very wide dynamic range, PSNR is usually expressed in terms of the logarithmic decibel scale.

The PSNR is most commonly used as a measure of quality of reconstruction in image compression etc. It is most easily defined via the mean squared error (MSE) which for two $m \times n$ monochrome images I and K where one of the images is considered a noisy approximation of the other is defined as:

$$MSE = \frac{1}{MN} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} \| I(i, j) - K(i, j) \|^2$$

The PSNR is defined as:

$$PSNR = 10 \log_{10} \left(\frac{MAX_1^2}{MSE} \right) = 20 \log_{10} \left(\frac{MAX_1}{\sqrt{MSE}} \right)$$

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

For color images with three RGB values per pixel, the definition of PSNR is the same except the MSE is the sum over all squared value differences divided by image size and by three.

An identical image to the original will yield an undefined PSNR as the MSE will become equal to zero due to no error. In this case the PSNR value can be thought of as approaching infinity as the MSE approaches zero; this shows that a higher PSNR value provides a higher image quality. At the other end of the scale an image that comes out with all zero value pixels (black) compared to an original does not provide a PSNR of zero [17][19]. This can be seen by observing the form, once again, of the MSE equation. Not all the original values will be a long distance from the zero value thus the PSNR of the image with all pixels at a value of zero is not the worst possible case.

3.4.2 Signal-to-noise ratio

It is an electrical engineering concept, also used in other fields (such as scientific measurements, biological cell signaling), defined as the ratio of a signal power to the noise power corrupting the signal.

In less technical terms, signal-to-noise ratio compares the level of a desired signal (such as music) to the level of background noise [31]. The higher the ratio, the less obtrusive the background noise is.

In engineering, signal-to-noise ratio is a term for the power ratio between a signal (meaningful information) and the background noise:

$$SNR = \frac{P_{Signal}}{P_{Noise}} = \left(\frac{A_{Signal}}{A_{Sinal}} \right)^2$$

Where P is average power and A is RMS amplitude. Both signal and noise power (or amplitude) must be measured at the same or equivalent points in a system, and within the same system bandwidth.

Because many signals have a very wide dynamic range, SNRs are usually expressed in terms of the logarithmic decibel scale. In decibels, the SNR is, by definition, 10 times the logarithm of the power ratio. If the signal and the noise is measured across the same impedance then the SNR can be obtained by calculating 20 times the base-10 logarithm of the amplitude ratio:

$$SNR(db) = 10\log_{10}\left(\frac{P_{Signal}}{P_{Noise}} \right) = 20\log_{10}\left(\frac{A_{Signal}}{A_{Noise}} \right)$$

In image processing, the SNR of an image is usually defined as the ratio of the mean pixel value to the standard deviation of the pixel values. Related measures are the "contrast ratio" and the "contrast-to-noise ratio". The connection between optical power and voltage in an imaging system is linear. This usually means that the SNR of the electrical signal is calculated by the 10 log rule[8][12][32]. With an interferometric system, however, where interest lies in the signal from one arm only, the field of the electromagnetic wave is proportional to the voltage (assuming that the intensity in the second, the reference arm is constant). Therefore the optical power of the measurement arm is directly proportional to the

electrical power and electrical signals from optical interferometer are following the 20 log rule. The Rose criterion (named after Albert Rose) states that an SNR of at least 5 is needed to be able to distinguish image features at 100% certainty. An SNR less than 5 means less than 100% certainty in identifying image details.

3.4.3 Mean Square Error

In statistics, the mean square error or MSE of an estimator is one of many ways to quantify the amount by which an estimator differs from the true value of the quantity being estimated. As a loss function, MSE is called squared error loss. MSE measures the average of the square of the "error" [9][10]. The error is the amount by which the estimator differs from the quantity to be estimated. The difference occurs because of randomness or because the estimator doesn't account for information that could produce a more accurate estimate [22]. The MSE is the second moment (about the origin) of the error, and thus incorporates both the variance of the estimator and its bias. For an unbiased estimator, the MSE is the variance. Like the variance, MSE has the same unit of measurement as the square of the quantity being estimated. In an analogy to standard deviation, taking the square root of MSE yields the root mean square error or RMSE, which has the same units as the quantity being estimated; for an unbiased estimator, the RMSE is the square root of the variance, known as the standard error.
Definition and basic properties
The MSE of an estimator θ′with respect to the estimated parameter θ is defined as

$$MSE(\theta') = E((\theta' - \theta)2).$$

The MSE can be written as the sum of the variance and the squared bias of the estimator

$$MSE(\theta') = Var(\theta') + (Bias(\theta', \theta))2.$$

The MSE thus assesses the quality of an estimator in terms of its variation
In a statistical model where the estimate is unknown, the MSE is a random variable whose value must be estimated. This is usually done by the sample mean

$$MSE^{'}(\theta^{'}) = \frac{1}{n}\sum_{j=1}^{n}(\theta_j - \theta)^2$$

With θ_j being realizations of the estimator θ′of size *n*.

3.5 Medical Image Compression with Region of Interest

In many Medical Applications, for fast interactivity while browsing through large sets of images (e.g. volumetric data sets, time sequences of images, image databases) or, for searching context dependent detailed image structures, and/or quantitative analysis of the measured data Compression is required. In medical imaging, the loss of any information when storing or transmitting an image is unbearable [10][26]. There is a broad range of medical image sources, and for most of them discarding small image details that might be an indication of pathology could alter a diagnosis, causing severe human and legal consequences. Data transmission and prioritization of regions of interests (ROIs) – and thus inherently support for lossy coding – are as important. Fast image inspection of large volumes of images transmitted over low bandwidth channels like ISDN, public switched telephone, or satellite networks (traditionally known as teleradiology), requires compression schemes with such progressive transmission capabilities. Moreover, optimal rate-distortion performance over the complete range of bit-rates that is requested by the application should also be considered. Additionally, the increasing use of three dimensional imaging modalities, like Magnetic Resonance Imaging (MRI), Computerized Tomography (CT), Ultrasound (US) triggers the need for efficient techniques to transport and store the related volumetric data. In order to decrease the volume of medical images, a context and ROI based approach is introduced. The ROI approach allows for important parts of an image to be coded with better quality than the rest of the image. The implementation of multi-ROIs medical image compression algorithm includes following 4 steps:

(1) Choose ROIs by hand: The automatic extraction of ROIs in medical image is a hot research area nowadays. ROI method that takes advantage of gray features of the medical image, which can be used to extract ROIs of large-scale medical images to a certain extent. However, there are so many different kinds of medical images which have different features, which make this ROI extraction method hard to be practical. To improve the robustness of extraction procedure, ROIs are selected by hand. After ROIs are determined, the relative position of ROIs is recorded. Assume that the image is divided into N-1 ROIs and one background area. These N-1 ROIs need to be encoded with different priorities. ROI priority determines the importance of a ROI in the image. The ROI having high priority means bit stream generated for this ROI will be appeared early in the whole image bit stream. The background area usually has lowest priority, which is appeared in final part of whole image bit stream.

(2) Image data separation: After choosing ROIs, image is divided into ROIs and non-ROIs. Non-ROIs are processed by wavelet transform first since coefficient matrix is required to be input of encoder. The processed coefficients are sent to ISPIHT encoder.

(3) Image compression: After the separation of image data, the coefficient matrix of image data is send to ISHIPT and get the corresponding bit streams.

(4) Bit stream integration: After the process of above steps, integrate all bit streams, which include ISPIHT bit stream, SPIHT bit stream and edge information made by canny operator.

Images can be split to

(1) Foreground

(2) Background.

- **Foreground (PROI)**

  The PROI is a main region of an image which can be annotated manually by radiologist, as illustrated in Fig. 1 or automatically by a computer aided detection system (CAD)[10]. The PROI contains important information, so this region should be kept without any loss of information. As described above, measuring the stenosis plays an important role for the diagnosis of PAD. For this reason, in our application, steno sis is a good candidate for PROI [10]. Therefore a lossless region based technique is applied to compress this part of the images.

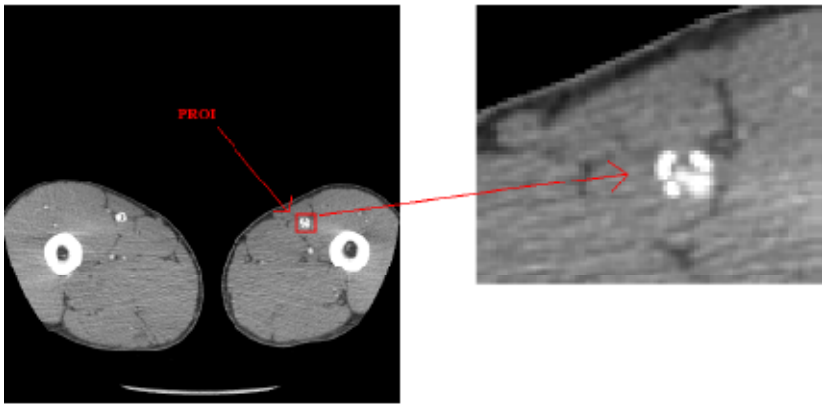


Fig 3.6: PROI

- **Background region**

  All area outside of human body is background as shown in Fig. 3. It does not carry relevant data, thus it is compressed with very high compression rate.

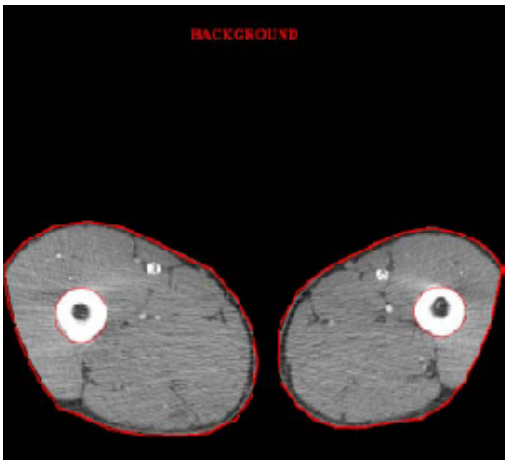


Fig 3.7: Background

CHAPTER: 4

Field Programme Gate Array

Introduction

An FPGA is a device that consists of thousands or even millions of transistors connected to perform logic functions. They perform functions from simple addition and subtraction to complex digital filtering and error detection and correction. Aircraft, automobiles, radar, missiles, and computers are just some of the systems that use FPGAs. A main benefit to using FPGAs is that design changes need not have an impact on the external hardware. Under certain circumstances, an FPGA design change can affect the external hardware.

4.1 A Short Historical Survey

By the early 1980s, most of the typical logic circuit systems were implemented within a small variety of standard large scale integrated (LSI) circuits: microprocessors, bus-I/O controllers, system timers, and so on. Nevertheless, every system still had the need for random “glue logic” to connect the large ICs, for example, generate global control signals and data formatting (serial to parallel, multiplexing, etc.) [15]. Custom ICs were often designed to replace the large amount of glue logic and consequently reduce system complexity and manufacturing cost, as well as improve performances. However, custom ICs are expensive to develop, while generating time-to-market (TTM) delays because of the prohibitive design time. Therefore the custom IC approach was only viable for products with very high volume (lowering the NRE cost impact), and not TTM sensitive. Coping with this problem, Xilinx TM (a start-up company) introduced, in 1984, the FPGA technology as an alternative to custom ICs for implementing glue logic. Thanks to computer-aided design (CAD) tools, FPGA circuits can be implemented in a relatively short amount of time: no physical layout process, no mask making, no IC manufacturing, lower NRE costs, and short TTM.

4.2 Basic FPGA Concepts

The basic FPGA architecture consists of a two dimensional array of logic blocks and flip-flops with means for the user to configure

(i) the function of each logic blocks,

(ii) the inputs/outputs, and

(iii) the interconnection between blocks (Figure 4.1).

Families of FPGAs differ from each other by the physical means for implementing user programmability, arrangement of interconnection wires, and basic functionality of the logic blocks.

4.3 Development Tools of FPGA

Each FPGA development phase utilizes specific tools, and they are discussed in the respective chapters. The design phase development tool depends mainly on the output format, but additional factors, such as cost, design sharing, and the need for it to be complete or standalone, can affect tool selection [15][18]. For example, if your design format is schematic capture, then the design entry tool must be one that supports schematic capture and not a text editor. On the other hand, it may be easier to use complete development tools over standalone ones.

- **Design format:** For HDL, any text editor will work., "Editor Features,"
- **Cost:** The fees for development tools can be very expensive, especially if they have yearly maintenance or licensing fees. Sometimes companies standardize the development tools, so you have no choice. But, if this is not the case, then I suggest having a clear understanding of your needs—try to get a temporary copy (i.e., try it before you buy it) and try to negotiate fees.
- **Design sharing:** For large designs that require multiple designers, your project may use tools that make it easy to divide the design among multiple people. So if this design has multiple coders, then you need a good set of tools to manage and control the design and its revisions.
- **Complete or standalone:** Some manufacturers offer complete development tools. For example, Xilinx's Integrated Software Environment and Altera's Quantus II are complete development tools. Standalone tools perform a single function, such as synthesis, implementation, or simulation. For example, Synopsys's Simplify is used for design synthesis and Mentor Graphic's ModelSim simulator is used for design verification, which means neither of these tools can perform the functions of the other. While it is true that some standalone tools, like ModelSim, provide a text editor that can be used to modify or create HDL code, the features and capabilities generally

are not as good as standalone or dedicated text editors. I do not suggest using that type of editor for design entry.

4.4 I/O Interfaces

I/O interfaces are the mediums in which data are sent from internal logic to external sources and from which data are received from external sources [21]. The interface signals can be unidirectional or bidirectional, single-ended or differential and could follow one of the different I/O standards. Some I/O standards are:

- GTL (gunning transceiver logic).
- HSTL (high-speed transceiver logic).
- LVCMOS (low-voltage CMOS).
- LVTTL (low-voltage transistor-transistor logic).
- PCI (peripheral component interconnect).
- LDT (lightning data transport).
- LVDS (low-voltage differential signaling).

The main purpose of the I/O interfaces is to transmit and receive data and basic building blocks are called configurable logic blocks.

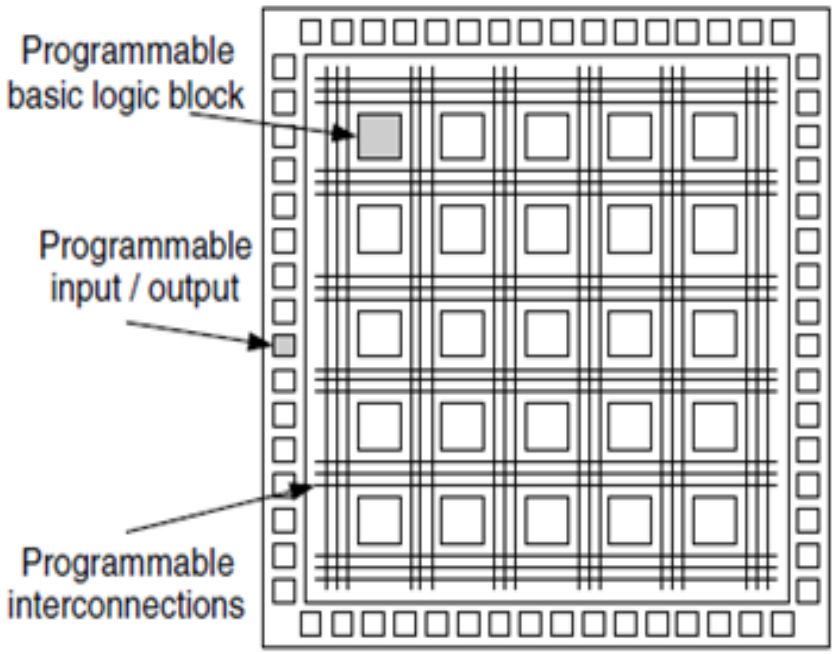


Fig 4.1: FPGA architecture

4.5 Simulation

Simulation is the process of applying stimulus or inputs that mimic actual data to the design and observing the output. It is used to verify that the design performs the expected and required functions. Inputs to the simulation phase can be the design phase output, synthesis net list, and implementation net list. Any one or all of these inputs can be used to perform simulation [15]. The output can be a listing, where the data are represented as binary, hex, or the like; graphically as a waveform; or the final results (such as pass/fail indicator), see Figure. Output from simulation is unique in that it does not feed into another development phase. However, the output is very important, because it provides the medium that allows the tester or verifier to see how the design performs.

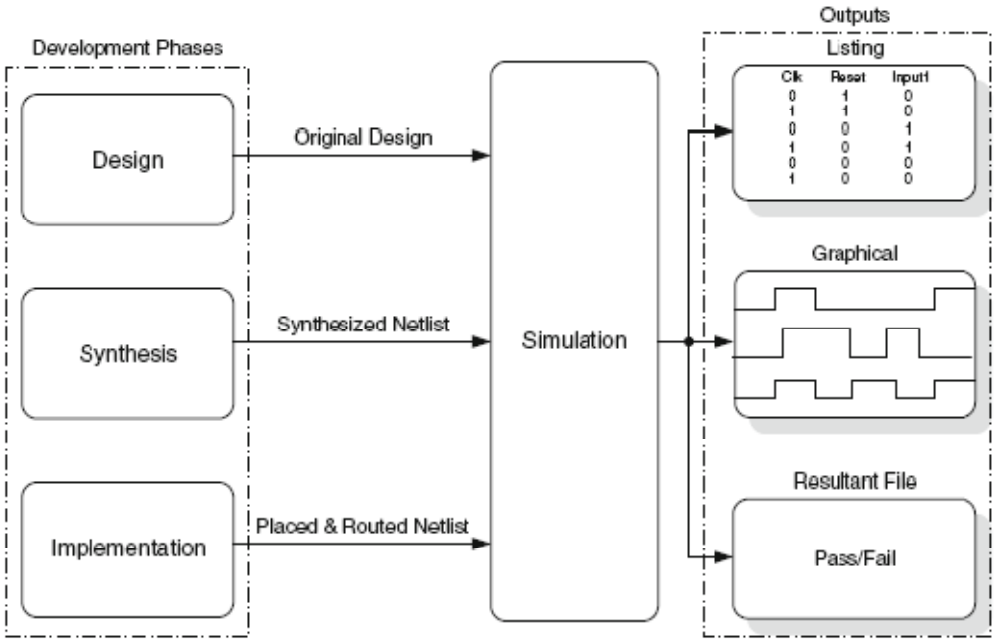


Fig 4.2: Simulation Phase Input Output:

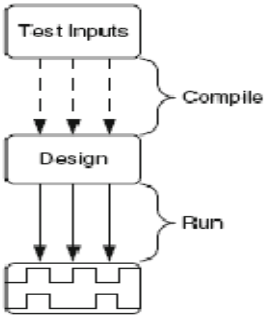


Fig 4.3: Simulation Tools

Levels of Simulation: There are three levels of simulation, see Figure 5–3: the register transfer level, gate level, and functional level.

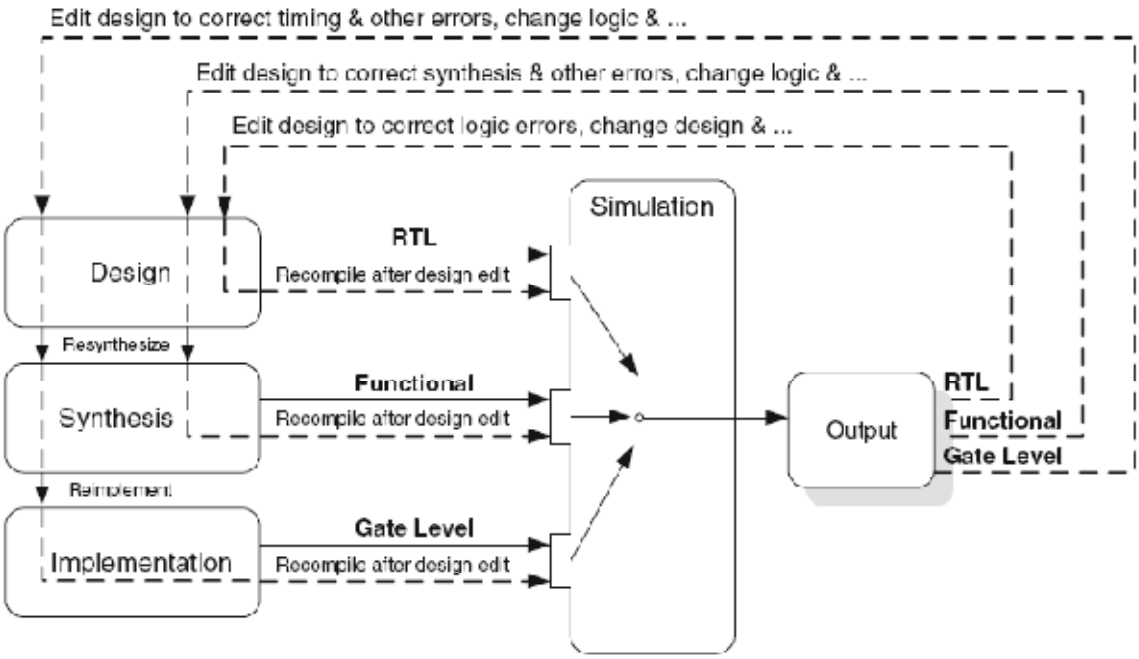


Fig 4.4: Simulation Level

4.6 Synthesis

Synthesis is the point in FGPA development where a high-level design is broken down into a mid-level net list that is now associated with logic and internal FPGA resources [18][29]. The design can be the one presented in this book or one you or someone else created or modified. It can be in several different formats—HDL, schematic capture, or a mixture—and may have been verified through simulation. In spite of whoever created or modified the design and the format, simulated or not, the design must be synthesized before it can be programmed into an FPGA. Although it could be performed immediately following the design phase. Once the design is complete it must somehow get broken down to a format that describes and connects the same funct ions in terms of FPGA resources and the design must go through a two-step process: first synthesis and then implementation. These steps take the high-level design and break it down to a format that eventually gets programmed into an FPGA.

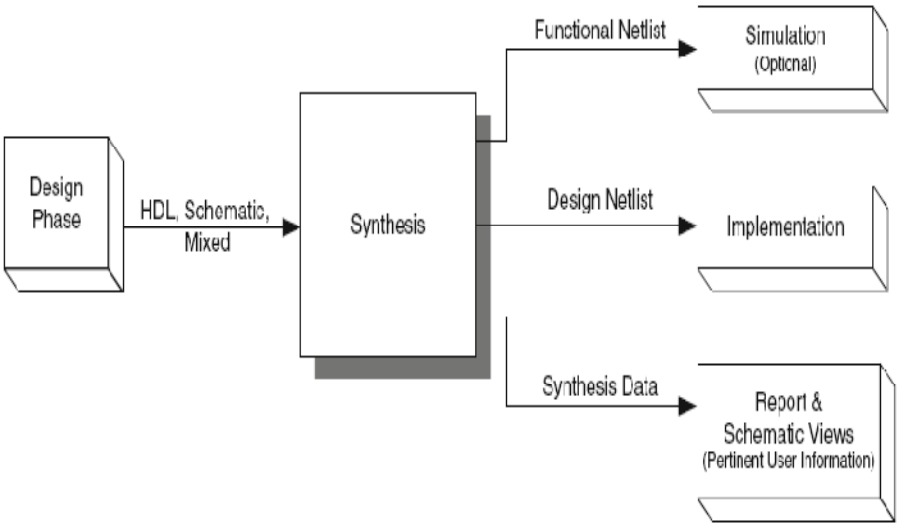


Fig 4.5: Synthesis Phase Input Output

Design synthesis or synthesis is the process that takes the high-level design associates it with FPGA resource and reduces logic to make the design more efficient. It can best be described as a three-step process that converts a high-level design to a mid-level design netlist, see Fig 4.5. Mid-level design netlist cannot be used to program an FPGA, but it is just one development stage from being ready to burn into a chip. Synthesis is the first step in the development process in which the design is associated with the FPGA's internal logic technology [21]. In other words, the output netlist is a little more realistic because the device's part number is defined and available resources are known and used to create the netlist that has some timing information. The three basic synthesis operations (Figure) are syntax check and element association, optimization, and technology mapping. Generic synthesis operation terms are used to distinguish one step from another.

4.7 Implementation

Implementation is the process that maps the synthesized netlist to the specific or target FPGA's resources and interconnects them to the FPGA's internal logic and I/O resources. During this process, the physical design layout is determined. This is the final development process that manipulates the design before it is programmed into a device. Each manufacturer performs implementation differently, but the concept is basically the same. The process described in this section is like the one performed by Xilinx's implementation tool. The implementation process takes four steps to convert the mid-level netlist to a final

programming file—translate, map, place and route, and generate programming file, see Fig 4.6.

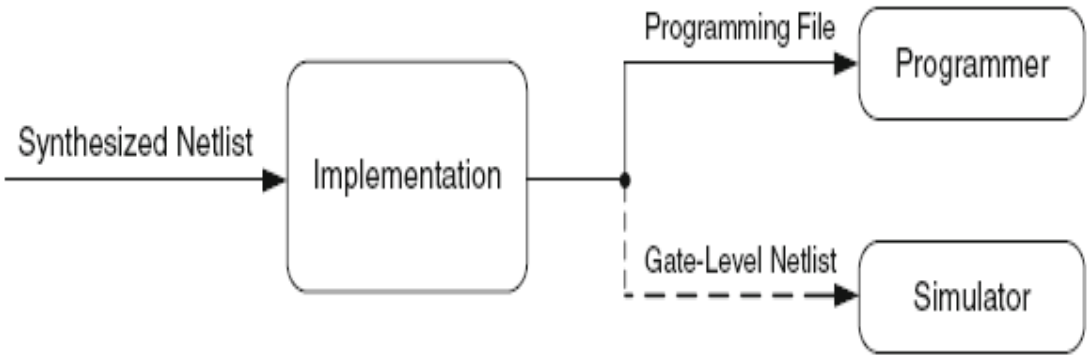


Fig 4.6: Implementation Phase Inputs and Outputs

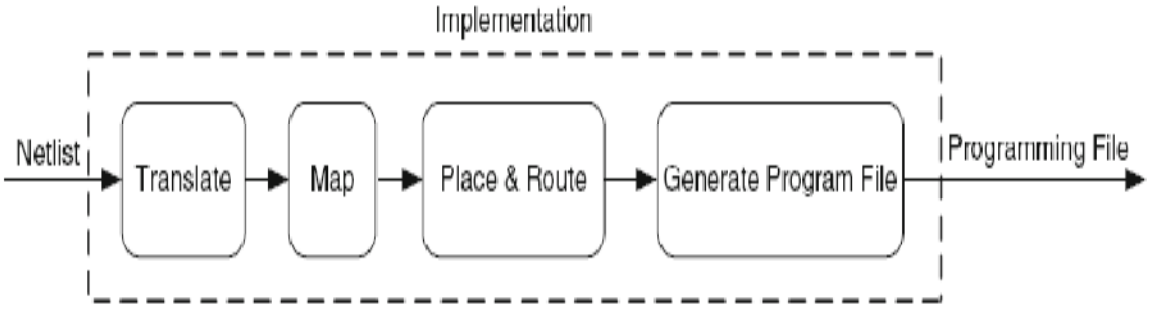


Fig 4.7: Implementation Steps

Implementation Outputs: Outputs from implementation are the bit stream file and an optional simulation netlist. Implementation also creates a lot of files and directories:

- Pin assignments.
- Timing information.
- Number of unrouted signals.
- Errors and warnings.
- Utilized resources.

Xilinx's ISE generates a report file for each of the implementation stages and several other different files within each stage:

1. Translate:

The translate process merges all of the input netlist and design constraint outputs a Xilinx NGD (Native information and Generic Database) file. The .ngd file describes the logical design reduced to the Xilinx device primitive cells. The output in the floor planner tool supplied with Xilinx ISE software. Here, defining constraints is nothing but, assigning the ports in the design to the physical elements (ex. pins, switches, buttons etc) of the targeted device and specifying time requirements of the design [27]. This information is stored in a file named UCF (User Constraints File). Tools used to create or modify the UCF are PACE, Constraint Editor Etc.

- Translate report.
- Floor plan design.
- Post-translation simulation model.

2. Map:

The map process is run after the translate process is complete. Mapping maps the logical design described in the NGD file to the components/primitives (Slices/CLBs) present on the NCD file created by the Map process to place and route the design on the target FPGA design. In this process the whole circuit is divided into sub blocks so that they can fit into FPGA logic blocks. The logic defined in the input NGD file is mapped into targeted FPGA elements i.e. CLBs and IOBs and an output NCD (native circuit description) file is generated which depicts the design mapped into the FPGA.

- Mapping report.
- Post-mapping static timing.
- Post-mapping floor plan design.
- Post-mapping simulation model.

3. Place and route:

After map the design is placed and routed. Place and Route **(**PAR) program is used for this process. The place and route process places the sub blocks from the map process into logic blocks according to the constraints and connects the logic blocks. Example if a sub block is placed in a logic block which is very near to IO pin, then it may save the time but it may affect some other constraint [21]. So tradeoff between all the constraints is taken account by the place and route process .The PAR tool takes the mapped NCD file as input and produces a completely routed NCD file as output. Output NCD file consist the routing information. During the place process the sub blocks are placed according to the

logic but these blocks do not have physical routing among them and with I/O pads also but there is only a logical connection between them which can be clearly seen using the FPGA Editor just after the place process ends. These logical connections are shown by rats nets in FPGA Editor. Then the Route process is run which makes physical connections between the sub blocks placed on FPGA. The connections are made using the switch matrices.

- Place-and-route report.
- Clock region report.
- Asynchronous delay report.
- Pad report.

4.8 Programming

In general, programming involves transferring the bit stream into a non-volatile or volatile memory device and configuring or programming the FPGA [15]. However, some FPGAs have internal memory and can hold the configuration without an external memory device. Input to the programming phase is a bit-stream or programming file and the output is a programmed device, see Fig 4.8.

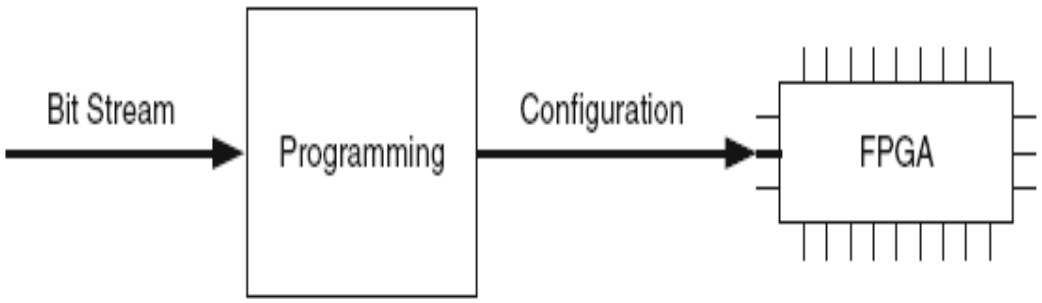


Fig 4.8: Programming Interfaces. Note: Multiple pins are represented by thick pin lines.

A two-step process is used to configure the FPGA with the bit-stream file when using an external memory device. In step first, the bit-stream file is transferred to the memory device; and in step second, the memory device configures the FPGA. A word to the wise, for parallel data transfers, make sure you know which bit is transmitted first

- Bit stream Generation: The collection of binary data used to program the reconfigurable logic device is most commonly referred to as a bit stream, although this is somewhat misleading because the data are no more bit oriented than that of an instruction set processor and there is generally no “streaming”. While in an instruction set processor the configuration data are in fact continuously streamed into the internal units, they are typically loaded into the reconfigurable logic device only once during an initial setup phase.
- A programming file is generated by running the Generate Programming File process. This process can be run after the FPGA design has been completely routed. The Generate Programming File process runs BitGen, the Xilinx bitstream generation program, to produce a bitstream (.BIT) or (.ISC) file for Xilinx device configuration. The FPGA device is then configured with the .bit file using the JTAG boundary scan method. After the Spartan device is configured for the intended design, then its working is verified by applying different inputs.

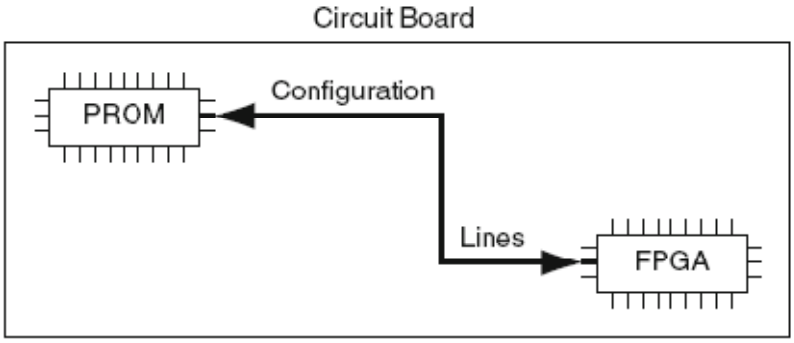


Fig 4.9: Non-volatile and FPGA on the Same Board.

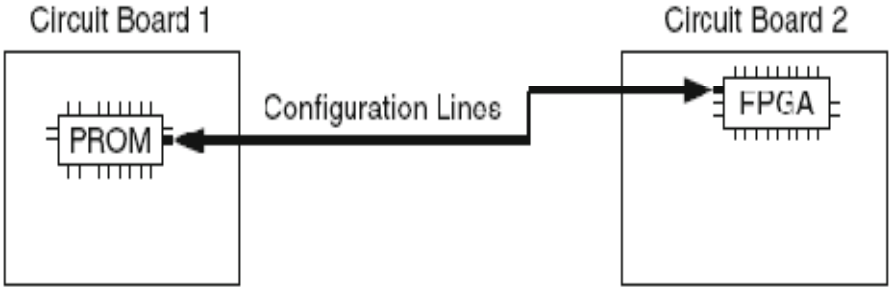


Fig 4.10: Non-volatile and FPGA on Different Boards.

Key Programming Phase Tips:

- Add test connectors, pins, and pads to the board to help with verification and troubleshooting.
- For parallel configuration, do not assume the order of data bit transfer.
- Select a memory device with sufficient room for growth.
- Make good use of configuration guides and other materials provided by the manufacturer.

4.9 Testing

- For a programmable device, you simply program the device and immediately have your prototypes. You then have the responsibility to place these prototypes in your system and determine that the entire system actually works correctly. If you have followed the procedure up to this point, chances are very good that your system will perform correctly with only minor problems. These problems can often be worked around by modifying the system or changing the system software. These problems need to be tested and documented so that they can be fixed on the next revision of the chip. System integration and system testing is necessary at this point to insure that all parts of the system work correctly together. When the chips are put into production, it is necessary to have some sort of burn-in test of your system that continually tests your system over some long amount of time [27]. If a chip has been designed correctly, it will only fail because of electrical or mechanical problems that will usually show up with this kind of stress testing.

CHAPTER 5

SIMULATIONS AND RESULTS

Image compression is the process of encoding information using fewer bits (or other information-bearing units) than any encoded representation would use, through use of specific encoding schemes. Image compression is minimizing the size in bytes of a graphics file without degrading the quality of the image to an unacceptable level. The reduction in file size allows more images to be stored in a given amount of disk or memory space. It also reduces the time required for images to be sent over the Internet or downloaded from Web pages. In this chapter Medical Images has been compressed through SPIHT and ROI and ISPIHT and ROI.

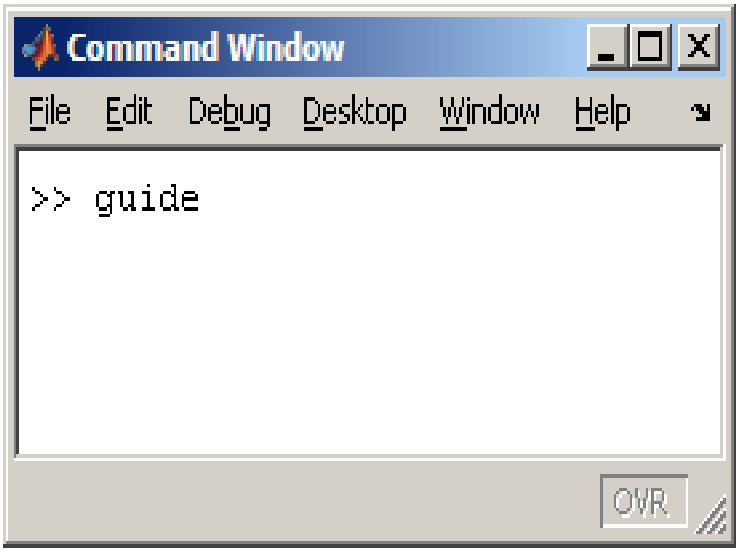


Fig 5.1: Command window

When guide on command window is written, the guide window will open which comprises of

1. Compression method
2. Operation
3. Peak signal to noise ratio and Bit per pixel
4. Browse option (to attach the .jpg file)

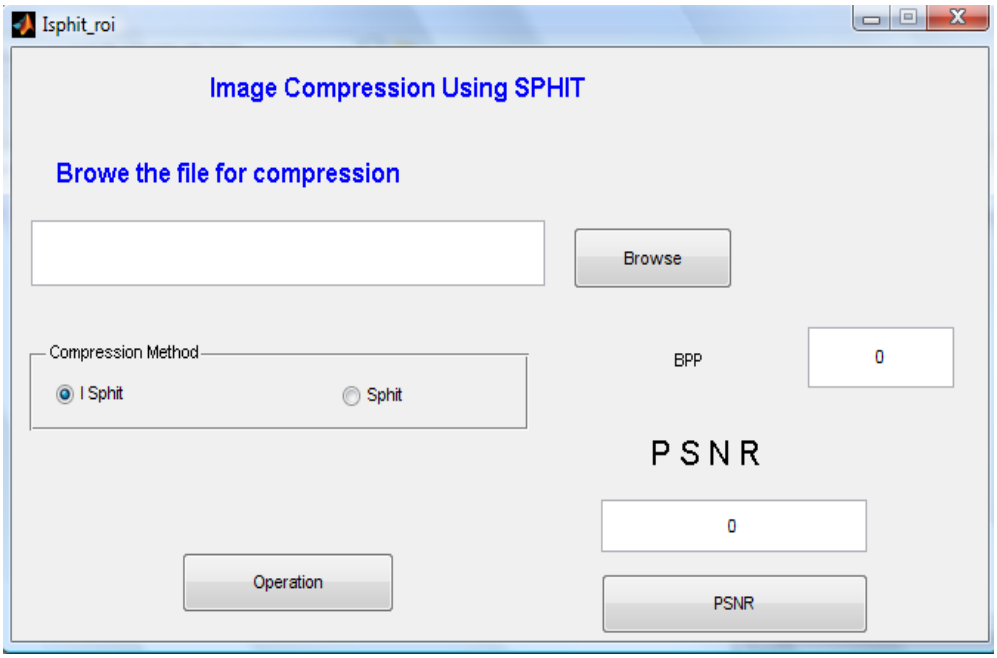


Fig 5.2: Guide Window

The guide window has SPIHT and ISPIHT options and either of them is to be selected, depending upon operation to be performed, before getting image of the given attached file.

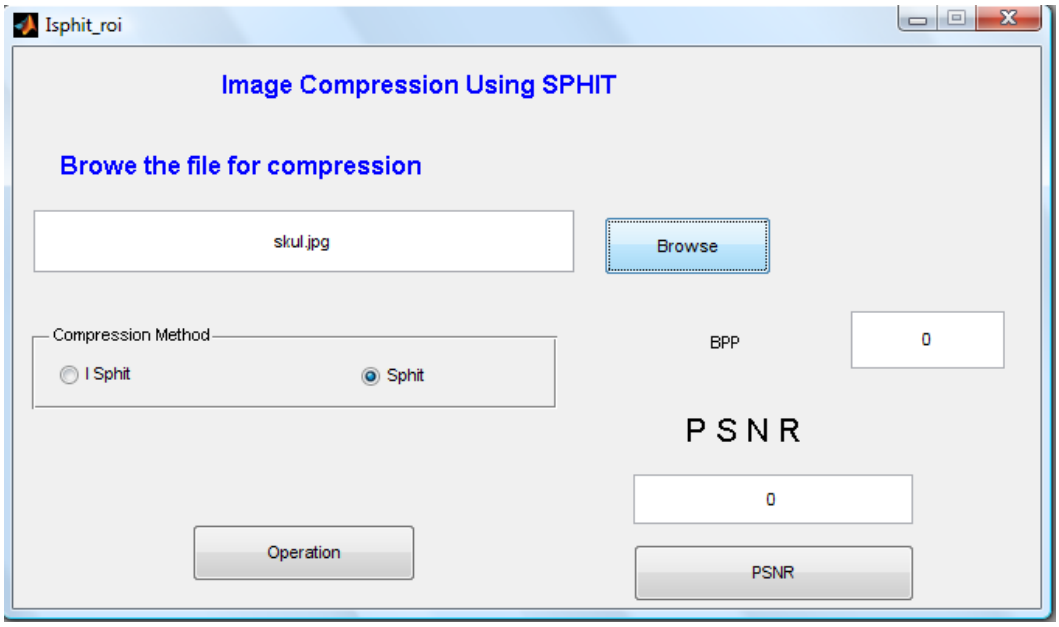


Fig 5.3: Guide Window After selects the Image

Now, as shown in next figure the Image window has option for reselect in which the doctor can select the particular region of interest (ROI) which he wants to go through and click for the compress option.

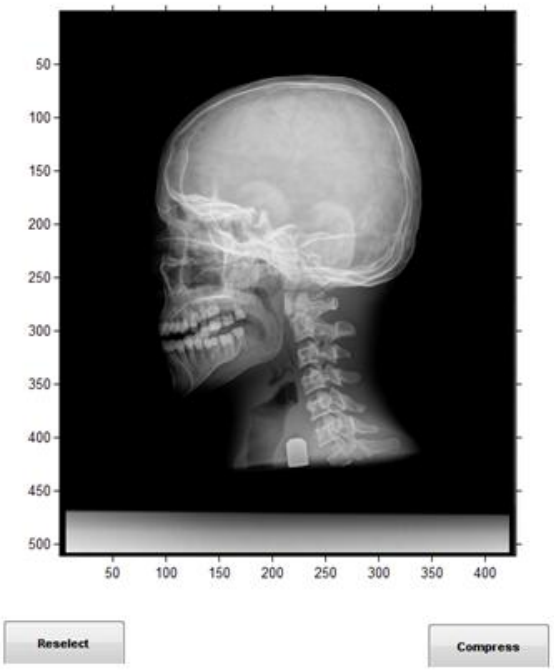


Fig 5.4: Image Window

Now, as shown in next figure, the compress Image is small in size in bytes of a graphics file without degrading the quality of the image. The original image size was 113 kb which reduced to 16.8 kb by SPIHT. It compress only background colour so that ROI region will not compress and hence improve its visibility.

Fig 5.5: Image Window after Select the ROI and operation Done

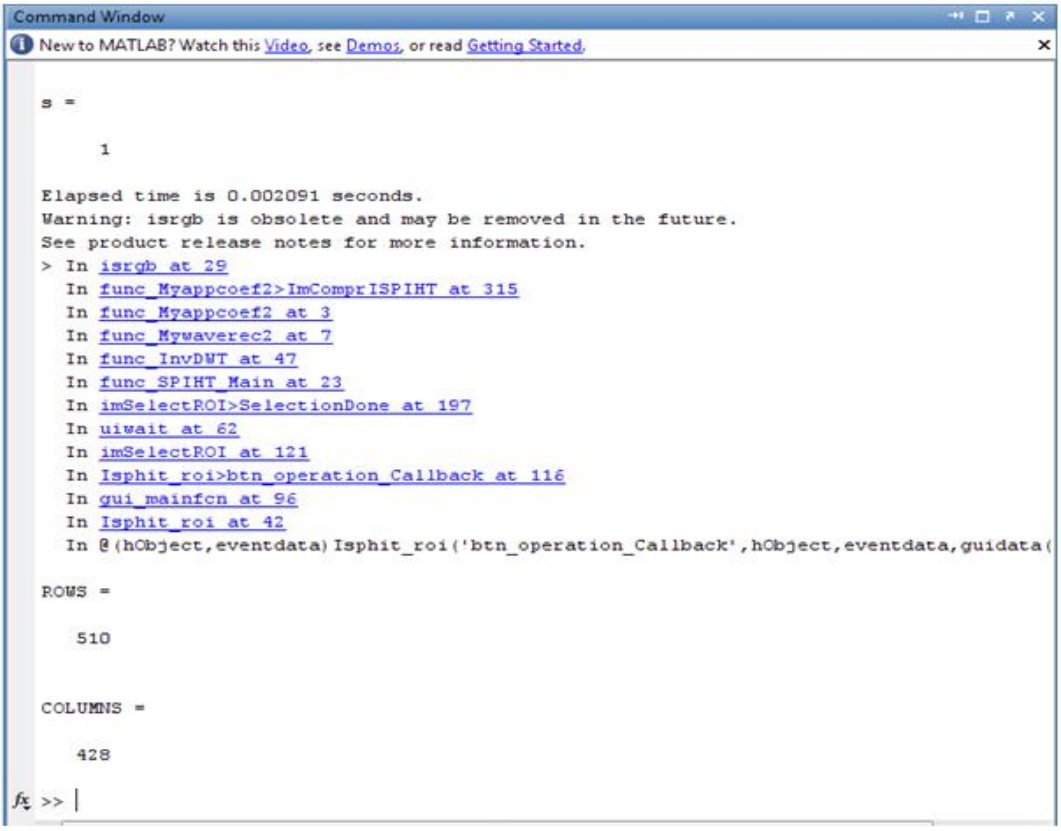


Fig 5.6: Command Window shows the No of Rows and Columns

Now figure 5.6 shows the no of rows and columns and total pixels which is multiplication of rows and columns. The pixels of the original image are converted into the coefficient of compressed image by the DWT. Result of DWT is shown in figure 9.

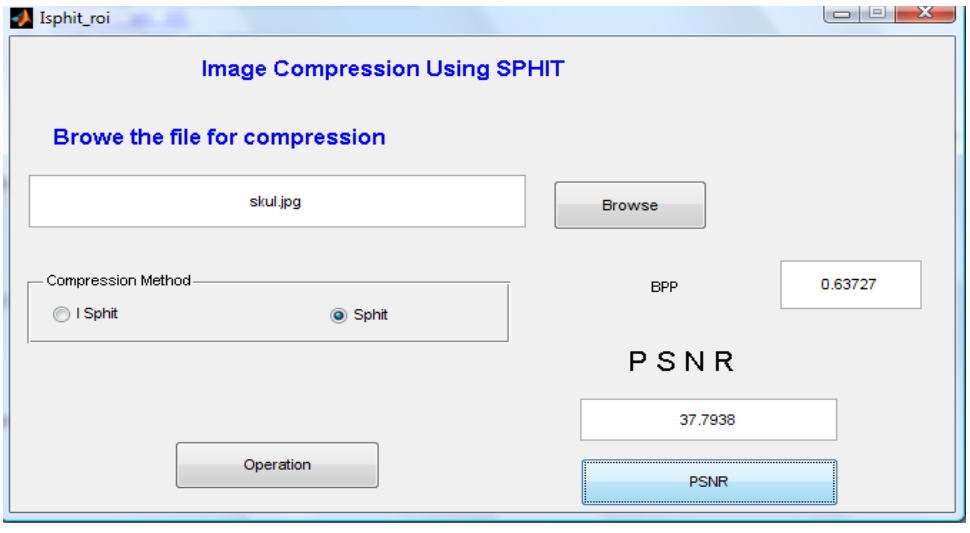


Fig 5.7: After Compres the Image PSNR and BPP

Figure 7 shows the peak signal to noise ratio of the compress image and bit per pixel also. Same result will be shown in the command window also as shown in fig 8.

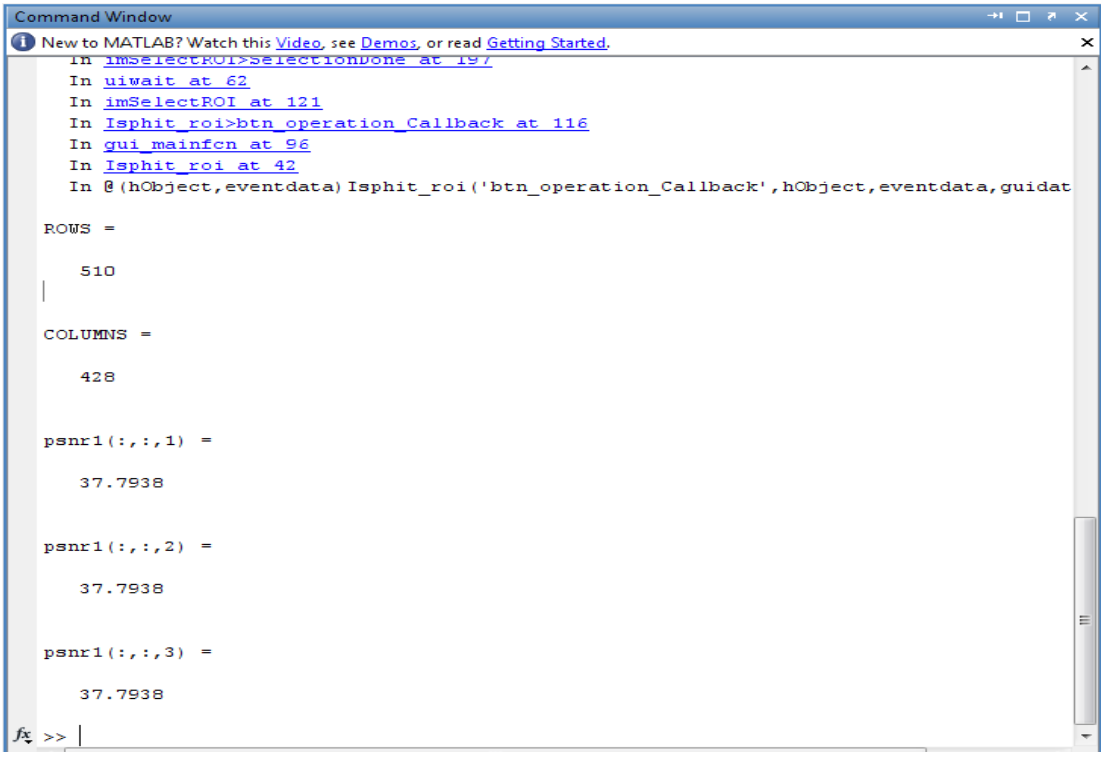


Fig 5.8: After Compres the Image PSNR and BPP in Command Window

These are the comparison of original image, SPIHT and ROI and Improved SPIHT and ROI. In Size, PSNR and BPP.

Fig : (A)
(Original Image)

Fig : (B)
(SPIHT and ROI)

Fig : (C)
(ISPIHT and ROI)

Table (i): Shows the comparison of Size,PSNR and BPP between original,SPIHT and ROI and ISPIHT and ROI

	Fig A	Fig B	Fig C
Size	113 kb	11.9 kb	11.6 kb
PSNR	-	37.004	41.355
BPP	-	0.637	0.643

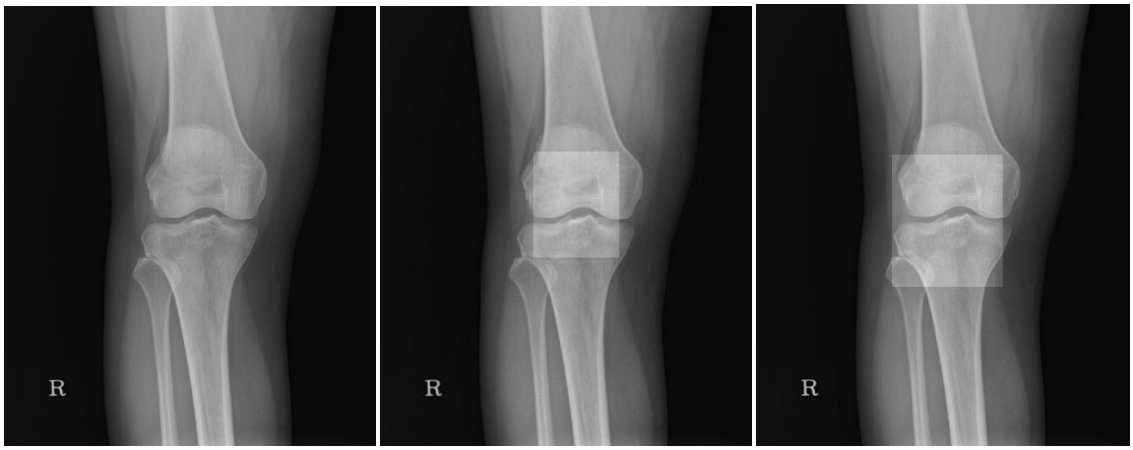


Fig : (A) Original Image of knee

Fig : (B) SPIHT and ROI

Fig : (C) ISPIHT and ROI

Table (ii): Shows the comparison of Size,PSNR and BPP between original,SPIHT and ROI and ISPIHT and ROI

	Fig A	Fig B	Fig C
Size	144 kb	12.0 kb	11.7 kb
PSNR	-	31.684	35.195
BPP	-	0.436	0.456

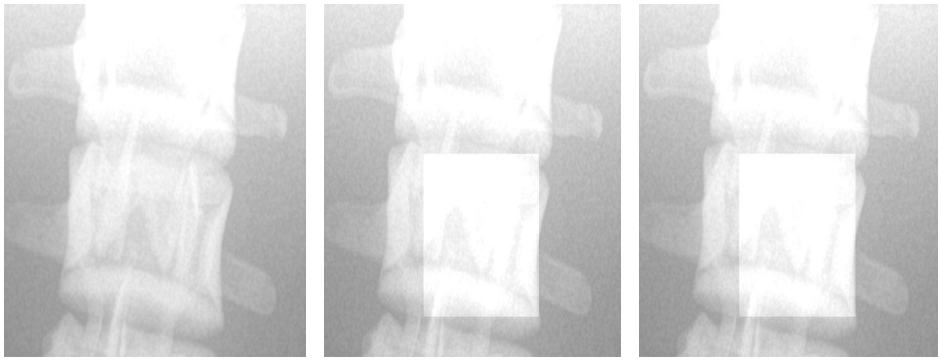


Fig : (A)

Fig : (B)

Fig : (C)

Table (iii): Shows the comparison of Size,PSNR and BPP between original spinal cord,SPIHT and ROI and ISPIHT and ROI

	Fig A	Fig B	Fig C
Size	210 kb	19.1 kb	18.3 kb
PSNR	-	25.971	33.358
BPP	-	0.545	0.568

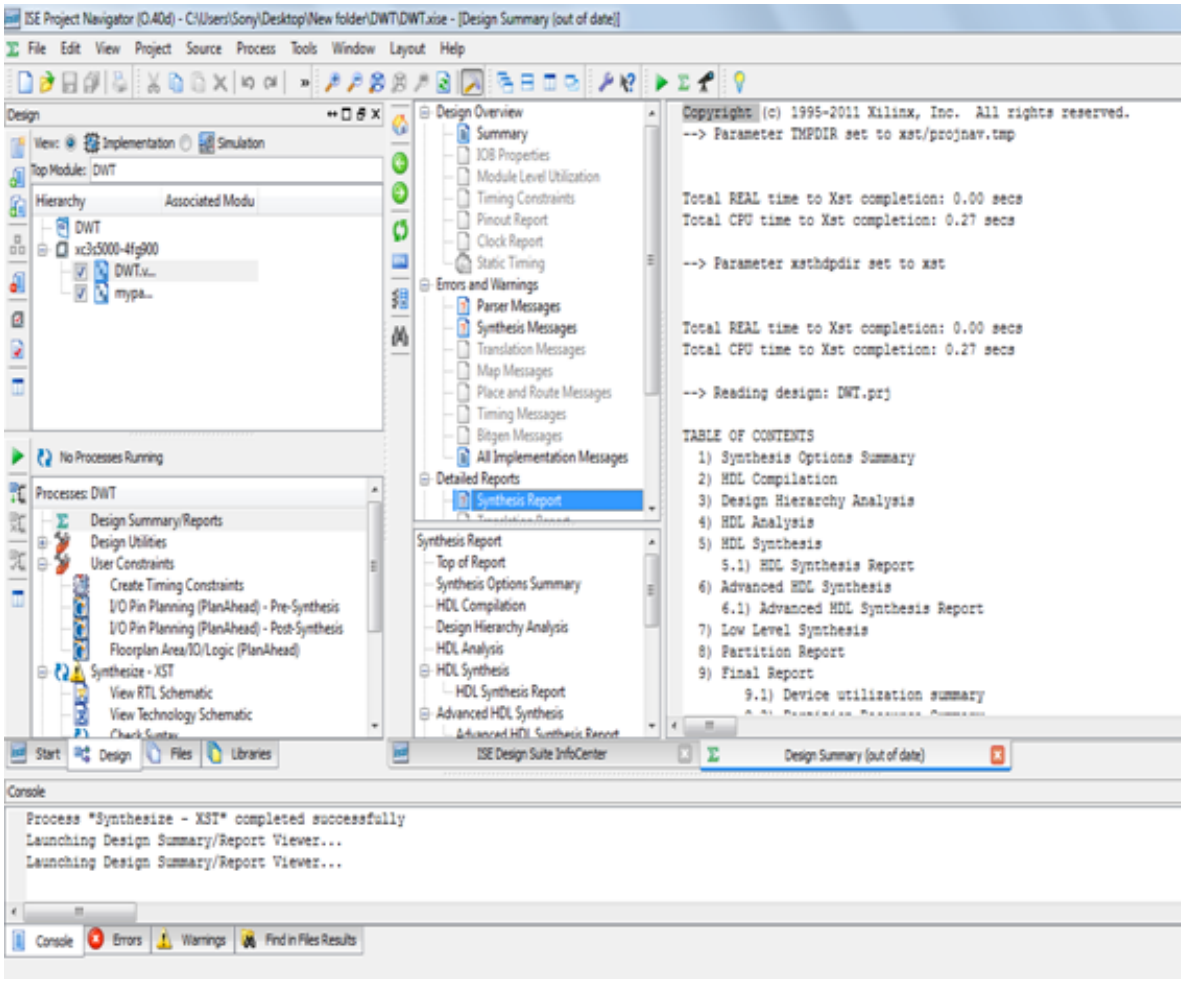


Fig 5.9: Shows the successefully running of DWT which converts the pixels into Coefficient

The result of the DWT is as following:

```
=========================================================================
*                      Final Report                     *
=========================================================================
Final Results
RTL Top Level Output File Name     : DWT.ngr
Top Level Output File Name         : DWT
Output Format                      : NGC
Optimization Goal                  : Speed
Keep Hierarchy                     : No
Design Statistics
# IOs                              : 682
Cell Usage :
# BELS                             : 686850
#      GND                         : 1
#      LUT1                        : 1184
#      LUT2                        : 230295
#      MUXCY                       : 223395
#      VCC                         : 1
#      XORCY                       : 231974
# IO Buffers                       : 682
#      IBUF                        : 341
#      OBUF                        : 341
# MULTs                            : 20
#      MULT18X18SIO                : 20
=========================================================================
Device utilization summary:
Selected Device                : 3s500efg320-4
 Number of Slices              : 117932  out of   4656   2532% (*)
 Number of 4 input LUTs        : 231479  out of   9312   2485% (*)
 Number of IOs                 : 682
 Number of bonded IOBs         : 682  out of    232   293% (*)
 Number of MULT18X18SIOs: 20  out of     20   100%
WARNING:Xst:1336 -  (*) More than 100% of Device resources are used
```

Partition Resource Summary:

No Partitions were found in this design.

==========

TIMING REPORT

NOTE: THESE TIMING NUMBERS ARE ONLY A SYNTHESIS ESTIMATE.

FOR ACCURATE TIMING INFORMATION PLEASE REFER TO THE TRACE REPORT

GENERATED AFTER PLACE-and-ROUTE.

Clock Information:

No clock signals found in this design

Asynchronous Control Signals Information:

No asynchronous control signals found in this design

Timing Summary:

Speed Grade: -4

Minimum period: No path found

Minimum input arrival time before clock: No path found

Maximum output required time after clock: No path found

Maximum combinational path delay: **1585.840ns.**

CHAPTER 6

CONCLUSION

SPIHT has many advantages, such as good image quality, high PSNR and good progressive image transmission. Hence, it also has wider application in the compression of images. A typical successful example was that an improvement to SPIHT has to be used to compress the images. Although the improvement made the memory space requirement to be optimized by some additional means.

In order to solve the memory space problem, a new algorithm using ISPIHT and ROI has been used in this research work. The size and execution time of this new algorithm is much less than that of the original one and the experimental results showed that the improved algorithm really improves the quality and size of images. The ROI of medical image has been used for the implementation of the compression algorithm. User can select ROI according to requirement and characteristic of medical image. The implemented algorithm employs a straightforward coding procedure, which lead to a low cost and simple hardware implementation.

The PSNR of compressed image has been calculated and is compared with the PSNR of image compressed through the SPIHT method only. At lower bit rates, the PSNR is almost identical for the original and modified versions but at higher bit rates, the PSNR is higher for the modified algorithm than the original one. Also the bit per pixel of image compressed through ISPIHT and ROI comes out to be better than that compressed through SPIHT only and it has been verified that bits per pixel remains directly proportional to PSNR.

References

[1] Yumnam Kirani Singh “ISPIHT-Improved SPIHT “A simplified and efficient subband coding scheme” Center for Development of Advanced Computing Plot: E-2/1, Block GP, Sector V, Salt Lake Electronics Complex.

[2] Hualiang Zhu, Chundi Xiu and Dongkai Yang “ An Improved SPIHT Algorithm Based on Wavelet Coefficient Blocks for Image Coding ” Beijing University of Aeronautics and Astronautics Beijing, P.R.China

[3] ASaid and W.APeariman, "A new fast and efficient image codec based on set partitioning in hierarchical trees," IEEE Trans. Circuits and Systems for Video Technology, vol. 6, no.3, pp.243-250, Jun.1996.

[4] A. Said,and W. A. Pearlman, “ A new, fast and efficient image code based on set partitioning in hierarchical trees”, IEEE Transactions on Circuits and Systems for Video technology, 1996, 6(6):243-250.

[5] J. H. Zhao, W. J. Sun, Z. Meng, Z. H. Hao, “Wavelet transform characteristics and compression coding of remote sensing images,” Optics and Precision Engineering, vol. 12(2), pp.205-210, 2004.

[6] H. L. Xu, S. H. Zhong, “Image Compression Algorithm of SPIHT Based on Block-Tree,” Journal of Hunan Institute of Engineering, vol. 19(1), pp.58-61, 2009.

[7] B. Yan, H. Zhang, “SPIHT Algorithm and its Improvement,” Computer Applications and Software, vol. 25(8), pp.245-247, 2008.

[8] F. W. Wheeler, and W. A. Pearlman, “SPIHT Image Compression without Lists,” IEEE Int. Conf on Acoustics, Speech and Signal Processing(ICASSP 2000). Istanbul: IEEE, 2000.2047-2050.

[9] Jianxiong Wang “Study of the Image Compression based on SPIHT Algorithm” college of water resources & hydropower and architecture, yunnan agriculture university Kunming.

[10] Min HU, Changjiang Zhang , Juan LU, Bo Zhou “A Multi-ROIs Medical Image Compression Algorithm with Edge Feature Preserving” Zhejiang normal university.

[11] Jia ZhiGang Guo XiaoDong Li LinSheng “A Fast Image Compression Algorithm Based on SPIHT ” College of Electronic and Information Engineering TaiYuan University of Science and Technology TaiYuan, ShanXi, China.

[12] Jianjun Wang “Modified SPIHT Based Image Compression Algorithm for Hardware Implementation” Xi’an Institute of Optics and Precision Mechanics Chinese Academy of Sciences Xi’an.

[13] LIU Wei “Research on Image Compression Algorithm Based on SPHIT” School of Equipment and Engineering ShenYang Ligong University Shenyang, P.R.China.

[14] Chunlei Jiang “A Hybrid Image Compression Algorithm Based on Human Visual System” Electrical and Information Engineering College Northeast Petroleum University Daqing, Heilongjiang Province.

[15] J. Jyotheswar, Sudipta Mahapatra “Efficient FPGA implementation of DWT and modified SPIHT for lossless image compression” Department of Electronics and Electrical Communication Engineering, IIT Kharagpur, Kharagpur 721 302, West Bengal Nov. 2006.

[16] Macarena Boix , Begoña Cantó “Wavelet Transform application to the compression of images” a Departamento de Matemática Aplicada, Universidad Politécnica de Valencia, Escuela Politécnica Superior de Alcoy, Plaza Ferrándiz y Carbonell 2, 03801 Alcoy (Alicante), Spain b Instituto de Matemática Multidisciplinar, Universidad Politécnica de Valencia, 46022 Valencia, Spain.

[17] Stephan Rein , Martin Reisslein,” Performance evaluation of the fractional wavelet filter: A low-memory image wavelet transform for multimedia sensor networks” a Telecommunication Networks Group, Technical University Berlin, Berlin b School of Electrical, Computer, and Energy Eng., Goldwater Center, MC 5706, Arizona State University, Tempe, AZ 85287-5706, United States.

[18] J. Jyotheswar, Sudipta Mahapatra “Efficient FPGA implementation of DWT and modified SPIHT for lossless image compression” Department of Electronics and Electrical Communication Engineering, IIT Kharagpur, Kharagpur 721 302, West Bengal, India.

[19] Peter Schelkens, Adrian Munteanu, Jan Cornelis “Wavelet-based compression of medical images: Protocols to improve resolution and quality scalability and region-of-interest coding” Department of Electronics and Information Processing (ETRO), Vrije Universiteit Brussel, Pleinlaan.

[20] Jose Oliver “A Fast Run-Length Algorithm for Wavelet Image Coding with Reduced Memory Usage” M.P. Malumbres Department of Computer Engineering (DISCA), Technical University of Valencia Camino de Vera 17, 46017, Spain.

[21] Pasquale Corsonello, Stefania Perrib, Paolo Zicari, Giuseppe Cocorullo “Microprocessor-based FPGA implementation of SPIHT image compression subsystems” a Department of Computer Science, Mathematics, Electronics and Transportation University of Reggio Calabria, Loc. Feo di Vito, 89060 Reggio Calabria, Italy Department of Electronics, Computer Science and Systems University of Calabria, Arcavacata di Rende.

[22] Nicholas Kolokotronis, Aliki Vassilarakou, Sergios Theodoridis, Dionisis Cavouras "Wavelet-based medical image compression Eleftherios Kofidis" Department of Informatics, Division of Communications and Signal Processing, University of Athens, Panepistimioupolis, TYPA Buildings, GR-15784 Athens, Greece .

[23] Lalitha Y. S, M.V.Latte "Lossless and Lossy Compression of DICOM images With Scalable ROI" Appa Institute of Engineering & Technology, Gulbarga, Karnataka, India. JSS Institute & Academy, Bangalore, India

[24] K.V.Sridhar, Prof. K.S.R.Krishna Prasa " MEDICAL IMAGE COMPRESSION USING ADVANCED CODING TECHNIQUE" National Institute of Technology, Warangal (AP)-India.

[25] A New Fast and Efficient "Image Codec Based on Set Partitioning in Hierarchical Trees "Amir Said Faculty of Electrical Engineering P.O. Box. State University of Campinas Brazil William A. Pearlman Department of Electrical Computer and Systems Engineering Rensselaer Polytechnic Institute.

[26] Rupinder Kaur, Nisha Kaushal "Comparative Analysis of Various Compression Methods for Medical Images" National Institute of Technical Teachers' Training & Research, Panjab university, Chandigarh, Dept. of Computer Science & Engineering (CSE).

[27] Nikola Sprljan, Sonja Grgic, Mislav Grgic "Modified SPIHT algorithm for wavelet packet image coding" Multimedia and Vision Lab, Department of Electronic Engineering, Queen Mary, University of London, London E1 4NS, UK Faculty of Electrical Engineering and Computing, University of Zagreb, Unska 3/XII, HR-10000 Zagreb, Croatia.

[28] Dr.S.Shenbaga Devi "Development of Medical Image Compression Techniques" Assistant Professor, College of Engineering Anna University Anna University Guindy, Chennai.

[29] Amir Said, W.A. Pearlman, "An image multiresolution representation for lossless and lossy compression", IEEE Trans. Image Processing, Vol. 5, pp. 1303-1310, 1996.

[30] Chun-Liang Tung, Tung-Shou Chen, Wei-Hua Wang and Shiow-Tyng Yeh, "A new improvement of SPIHT progressive image transmission," Proceedings of the IEEE Fifth International Symposium on Multimedia Software Engineering, IEEE Press,Taichung, Taiwan ,Dec, 2003, pp ISO-IS7

[31] ASaid and W.APeariman, "A new fast and efficient image codec based on set partitioning in hierarchical trees," IEEE Trans. Circuits and Systems for Video Technology, vol. 6, no.3, pp.243-250, Jun.1996.