HARDWARE IMPLEMENTATION OF IMAGE COMPRESSION USING RIPPLET TRANSFORM

Main Project Report

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BONAFIDE CERTIFICATE

This is to certify that the Project report entitled

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Submitted by

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is a bonafide account of the work done by them under our supervision.

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ABSTRACT

Images are now an important part of our lives. It is used in different domains.This increases the difficulties for a storage system to store, manage and to transmit these images. Among the proposed compression methods, much interest has been focused on achieving good compression ratios and high Peak Signal to Noise Ratio (PSNR), and little work has been done on resolving 2D singularities along image edges with efficient representation of images at different scales and different directions. Grounded on this fact, this paper proposes a compression method for medical images by representing singularities along arbitrarily shaped curves without sacrificing the amount of compression. This method uses a recently introduced family of directional transforms called Ripplet transform. Usually the coarser version of an input image is represented using base, but discontinuities across a simple curve affect the high frequency components and affect all the transform coefficients on the curve. Hence these transforms do not handle curve discontinuities well. By defining the scaling law in a more broader scope and more flexible way, Ripplet Transform is formed as a generalisation of Curvelet transform, by adding two tunable parameters i.e support of Ripplets and degree of Ripplets.Further this project implements this compression technique on fpga for to increase its speed and thus will create an image compression engine.

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List of Abbreviations

BCS - Block Compressive Sensing

BPDN - Basis Pursuit Denoising

CS - Compressive sensing

CT - Computed Tomography

FISTA - Fast Iterative Shrinkage Thresholding Algorithm

IHT - Iterative Hard Thresholding

ISTA - Iterative Shrinkage Thresholding Algorithms

JASR - Joint Adaptive Sparsity Regularization

LASSO - Least Absolute Shrinkage and Selection Operator

LSMM - Local Structural Measurement Matrix

MR - Measurement Ratio

Chapter 1

INTRODUCTION

From early days to now, the basic objective of image compression is the reduction of size for storage while maintaining suitable quality of decoded images. Compression not only minimizes channel capacity and storage requirements but also reduces time required to transmit data. Consequently, the methods of compressing data prior to storage and transmission are of significant practical and commercial interest. Most compression schemes are lossy,where high compression ratios are gained by sacrifice of the original data within certain allowable degradation limits. However, many important and diverse applications, including medical imaging, satellite, aerial imaging image archiving, and precious fine arts and documents preserving, or any application demanding ultra high image fidelity, require lossless compression (i.e, reconstruct the compressed data without any loss of information).In Image processing, Fourier transform is usually used for image representation in tradition. However, Fourier transform can only provide an effient representation for smooth images but not for images that contain edges. Edges or boundaries of objects cause discontinuities or singularities in image intensity. But singularities in a function (which has finite duration or is periodic) destroy the sparsity of Fourier series representation of the function, which is known as Gibbs phenomenon [1]. In contrast, wavelet transform is able to efficiently represent a function with 1D singularity. Currently, the most popular choice is wavelet transforms. However, typical wavelet transform is unable to resolve two dimensional (2D) singularities along arbitrarily shaped curves. In order to overcome this weakness, a new system of representations namely ridgelet which can effectively deal with linelike phenomena in 2D, was proposed.

However, to overcome the limitations of these transforms, a theory called Multiscale Geometric Analysis (MGA) theory has been developed for high dimensional signals and several MGA transforms are proposed such as contourlet, curvelet, bandelet, etc. The ridgelet transform also fails to resolve 2D singularities. In order to analyze local line or curve singularities, there is an idea to partition the image, similar to block processing and then to apply ridgelet transform to the obtained sub - images. This multiscale ridgelet transform is proposed by Starck and named as curvelet transform [2]. The curvelet transform represents two dimensional functions with smooth curve discontinuities at an optimal rate. Contourlets, as proposed by Do and Vetterli [3] form a discrete filter bank structure that can deal effectively with piece-wise smooth images with smooth contours. Contourlet has less clear directional features than curvelet, which in turn leads to artifacts in image compression. Ripplet-I transform adds two parameters, i.e., support c and degree d to the Curvelets. Ripplet-I is provided with anisotropic capability of representing 2D singularities along arbitrarily shaped curves, by the introduction of these parameters. Images are approximated from coarse to fine resolutions and is represented hierarchically by the Ripplet transform. Higher energy compaction is achieved as the transform coefficients decay faster than any other transforms. Good localization in both spatial and frequency domains makes it compactly supported in the frequency domain and fastly decaying in the spacial domain.The ripplet functions orient at various directions as the resolution increases. The anisotropy of ripplet functions is a result of the general scaling and support that guarantees to capture singularities along various curves.

Chapter 2

LITERATURE SURVEY

During these past years lots of transform has been introduced for the co compression of images. In image process sing, Fourier transform is the first conventional method used. But the Fourier transforrm is suitable only for an efficient representation of smooth images but not for images that contain edges. The (1D) singularity in a function destroys the sparsity of Fourier series representation of the function. Next comes, the wavelet transform which is able to efficiently y represent a function with 1D singularity. But the wavelet transform is unable to o resolve two dimensional (2D) singularities along arbitrarily shaped curves. Since 2D wavelet transform is just a tensor product of two 1D wavelet transform ms, it resolves 1D horizontal and vertical singularities, respectively. The poor directionality of wavelet transform has undermined its usage in many applications. To overcome the limitation n of wavelet, Multiscale Geometric Analysis (MGA) theory has been developed for high dimensional signals and several MGA transforms are proposed such as ridgelet, curvelet, contourlet, surfacelet and bandelet. Ridgelet transform can resolve 1D singularities along an arbitrary direction. Since ridgelet transform is not able to resolve 2D singularities, Candes and proposed the first generation curvelet transform based on multiscale ridgelet. In order to analyze local line or curve singularities, the idea is to partition the image, and then to apply ridgelet transform to the obtained subimages. This multiscale ridgelet transform is proposed by Starck et al.and named as curvelet transform. The curvelet transform represents two dimensional functions with smooth curve discontinuities at an optimal rate. In order to optimize the scaling law, the Ripplet transform is proposed. The proposed Ripplet transform provides better performance than the directional transforms because it localizes the singularities more accur rately and is highly directional to capture the orientations of singularities.

Binit Amin, Patel Amrutbhai proposed a method based on Vector Quantization and by using wavelets. This work informs a survey on Vector quantizations based lossy image compression usingwavelets.Vector quantization has the potential to greatly reduce the amount of information required for an image because it compresses in vectors which provides better efficiency than compressing in scalars. Vector quantization based coded images then encoded for transmission by using different encoding technique like Huffman encoding, Run Length Encoding etc. Manpreet Kaur and Vikas Wasson proposed a compression method based on Region of Interest (ROI) of an image. In medical field only the small portion of the image is more useful. The reason behind for including the regions other than ROI is to make user as more easily to locate the position of critical regions in the original image. But for medical images this will be a risk as the vital information cannot be preserved using ROI method. Sujitha Juliet, Blessing Rajsingh and Kirubakaran Ezra proposed a compression method based on projection [7].This method takes advantage of the Radon transform and its basis functions are effective in representing the directional information. The technique computes Radon projections in different orientations and captures the directional features of the input image. But the method fails to represent edge features effectively.

Chapter 3

TRANSFORMS USED NOW

3.1 Fourier Transform

The Fourier transform is probably the most widely applied signal processing tool in science and engineering. It reveals the frequency composition of a time series by transforming it from the time domain into the frequency domain. An aperiodic signal can be represented by a weighted integral of a series of sine and cosine functions. Such an integral is termed the Fourier transform. The Fourier transform of a signal can be expressed as

$$X(f) =< x, e^{i2\pi f} >= \int_{-\infty}^{+\infty} x(t)e^{i2\pi f(}t)dt \tag{3.1}$$

Assuming that the signal has finite energy

$$\int_{-\infty}^{+\infty} |x(t)|^2 < 0 \tag{3.2}$$

Accordingly, the inverse Fourier transform of the signal can be expressed as

$$X(t) = \int_{-\infty}^{+\infty} x(f)e^{-i2\pi ft}df \tag{3.3}$$

Signals obtained experimentally through a data acquisition system are generally sampled at discrete time intervals âˆ†T within a total measurement time T. Such a signal, can be transformed into the frequency domain by using the Discrete Fourier Transform (DFT). Basis functions employed in DFT are complex sinusoids. By computing the DFT of a signal, it is decomposed into its individual, N frequency components,$w_k = \frac{2\pi k}{N}$ DFT coefficients depict the relative significance or contribution of each frequency component represented as complex sinusoid. For this reason, DFT domain is sometimes referred to as frequency domain.

3.2 Wavelet Transform

Varying time and frequency resolution is possible in wavelet transform (WT). The analysis is carried out with scaled and shifted versions of basis function called wavelet. Wavelets are functions that satisfy certain requirements. The very name comes from the requirement that they should integrate to zero, waving above and below x-axis. The other requirements are technical and needed mostly to insure quick and easy calculations of direct and inverse wavelet transforms.

The wavelet analysis procedure is to adopt a wavelet prototype function called analyzing wavelet or mother wavelet. Temporal analysis is performed with a contracted, high-frequency version of the prototype wavelet, while frequency analysis is performed with a dilated, low-frequency version of the same wavelet.Because the original signal or function can be represented in terms of a wavelet expansion, data operations can be performed using just the corresponding wavelet coefficients. If the wavelet function chosen is best adapted to the data or if the coefficients are truncated below threshold value then the data can be sparsely represented.

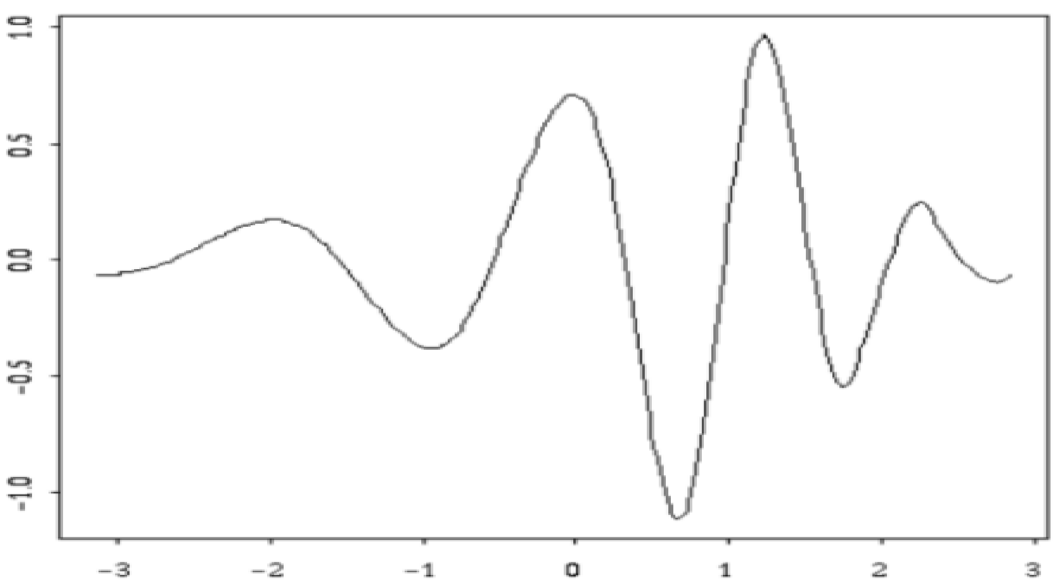

Figure 3.1: Wavelet from Daubechies family

Scaling and shifting of wavelet during signal analysis results in variable time and frequency resolution. The basis function can be stretched or compressed dynamically by varying dilation parameter â˜aâ^{TM} kernel can be shifted anywhere in the time domain dynamically by varying translation parameter â˜bâ^{TM}. Thesetwo features result in variable time and frequency resolution. Thus, it is a technique that catches the rhythm of the signal. Thus, WT behaves as a mathematical microscope.The wavelet transform of a signal can be expressed as

$$wt(s,\tau) =< x, \Psi_{s,t} >= \frac{1}{\sqrt{a}}\int_{-\infty}^{+\infty} x(t)\Psi^*(\frac{t-a}{b})dt \tag{3.4}$$

Through variations of the scales and time shifts of the base wavelet function, the wavelet transform is capable of extracting the constituent components within a time series over its entire spectrum, by using small scales (corresponding to higher frequencies) for decomposing high frequency components and large scales (corresponding to lower frequencies) for low frequency components analysis. The wavelet function can be chosen based on the characteristics of signal under analysis. As the time width of the window reduces, frequency resolution becomes poor and vice versa. It implies that WT cannot discriminate signals with too close high frequencies. Uniqueness of WT is that it does not have a unique basis function. It can be selected depending on the signal. This feature helps in catching up with the rhythm of the signal. It localizes events in time and frequency domain.

3.3 Ridgelet Transform

Wavelets are nongeometrical and do not exploit regularity of edge curve as the wavelet bases are made of local isotropic oscillatory bumps at various scales, and are not adapted to represent long elongated structures like edges. Wavelets are highly adapted for point singularities whereas for higher dimensions they are poorly adapted. Wavelets relay on dictionary of roughly isotropic elements occurring at all scales and locations, they do not describe well highly anisotropic elements and contains only fixed number of directional elements, independent of scales. So wavelet coefficients can offer sparsity only in analyzing objects with punctuated smoothness.

$$CRT_f(a,b,\theta) = \int_{R^2} \Psi_{a,b,\theta}(x) f(x) dx \tag{3.5}$$

where the ridgelets $\Psi_{a,b,\theta}(x)$ in 2-D are defined from a wavelet-function in 1-D $\Psi_{a,b,\theta}(x)$ as

$$\Psi_{a,b,\theta}(x) = a^{-1/2}\Psi((x_1 \cos\theta + x_2 \sin\theta + b)/a) \tag{3.6}$$

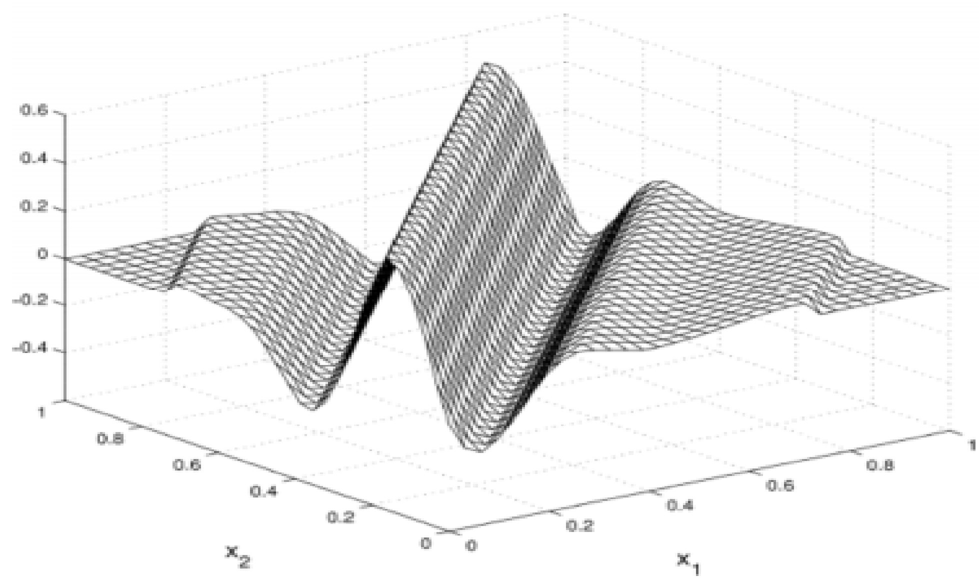

Figure 3.2: Ridgelet in 2D plan

Ridgelet analysis may be constructed as wavelet analysis in the Radon domain. The rationale behind this is that the Radon transform translates singularities along lines into point singularities, for which the wavelet transform is known to provide a sparse representation.

3.4 Curvelet Transform

The curvelet transform is a multiscale directional transform, which allows an almost optimal nonadaptive sparse representation of objects with edges. Curvelets provide an effective model that considers a multiscale time-frequency local partition and also makes use of the direction of features.Wavelets perform well only at representing point singularities, since they ignore the geometric properties of structures and do not exploit the regularity of edges. But most natural images exhibit line like edges.So wavelet-based compression, denoising, or structure extraction become computationally inefficient for geometric features with line and surface singularities.

The needle-shaped elements of curvelet transform possess very high directional sensitivity and anisotropy. Such elements are very efficient in representing line like edges.Curvelet transform uses angled polar wedges or angled trapezoid windows in frequency domain in order to resolve also directional features.

Anisotropic geometric wavelet transform, known as ridgelet transform, is optimal at representing straight-line singularities. Unfortunately, the ridgelet transform is only applicable to objects with global straight-line singularities. In order to analyze local line or curve singularities, ridgelet transform is applied to the partitioned image to obtain sub-images. This block based ridgelet transform, is the first generation curvelet transform. Since the geometry of ridgelets is not well defined, the application of first generation curvelet transform is limited.Second generation curvelet transform based on a frequency partition technique.Here the discrete cosine domain is tiled instead of the discrete Fourier domain to adequately reorganize the data.

Multiscale decomposition captures point discontinuities into linear structures.Curvelets in addition to a variable width have a variable length and so a variable anisotropy. The length and width of a curvelet at fine scale due to its directional characteristics is related by the parabolic scaling law:

$$width = (length)^2 \tag{3.7}$$

Curvelets partition the frequency plan into dyadic coronae that are sub partitioned into angular wedges displaying the parabolic aspect ratio as shown in fig.Curvelets at scale 2^{-k} are of rapid decay away from a "ridge" of length $2^{-k/2}$ and width 2^{-k} and this ridge is the effective support.The discrete translation of curvelet transform is achieved using wrapping algorithm. The curvelet coefficients C_k for each scale and angle is defined in Fourier domain by

$$C_k(r,\theta) = 2^{-3k/4} R(2^{-k}r) A(2^{k/2}/2\pi\theta) \tag{3.8}$$

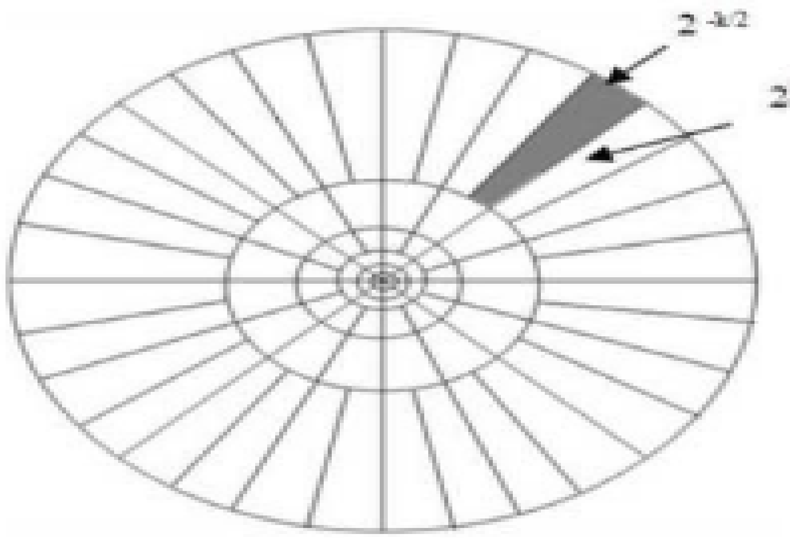

Figure 3.3: Curvelets in Frequency Domain

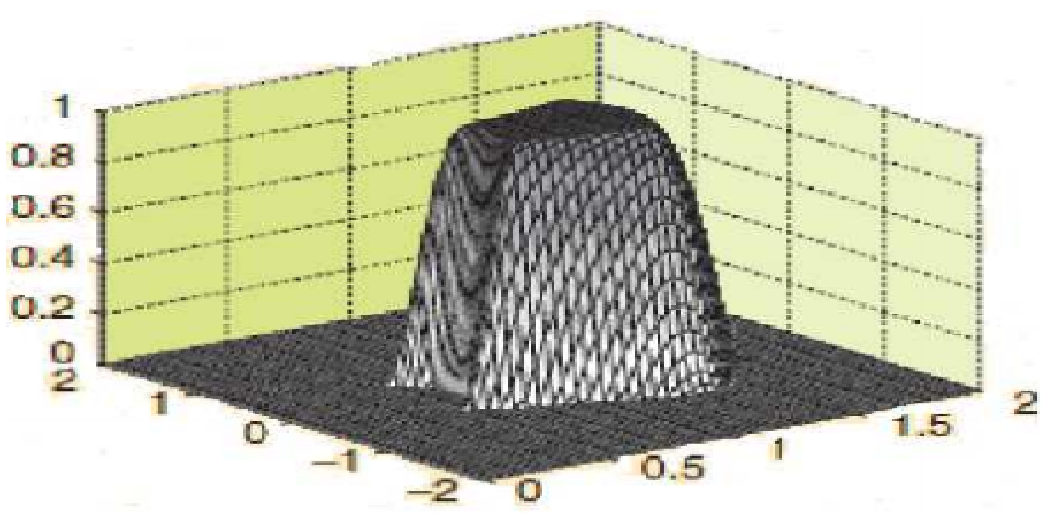

Figure 3.4: Basic Curvelet Element

Chapter 4

RIPPLET TRANSFORM

Efficient representation of images or signals is critical for image processing, computer vision, pattern recognition, and image compression. Fourier transform is traditionally used to efficiently represent a signal as a weighted sum of basis functions. However, Fourier transform can only provide an efficient representation for smooth images but not for images that contain edges. Edges or boundaries of objects cause discontinuities or singularities in image intensity. One-dimensional

(1D) singularities in a function destroy the sparsity of Fourier series representa- tion of the function, which is known as Gibbs phenomenon.In contrast, wavelet

transform is able to efficiently represent a function with 1D singularities. However, typical wavelet transform is unable to resolve two-dimensional (2D) singularities along arbitrarily shaped curves.

To overcome the limitation of wavelet, ridgelet transform was introduced. Ridgelet

transform can resolve 1D singularities along an arbitrary direction. Ridgelet trans- form provides information about orientation of linear edges in images. Since ridgelet

transform is not able to resolve 2D singularities, curvelet transform was proposed. Curvelet transform can resolve 2D singularities along smooth curves. Curvelet transform uses a parabolic scaling law to achieve anisotropic directionality. The anisotropic property of curvelet transform guarantees resolving2D singularities along C_2 curves.

To address the problem of conventional transforms a new Multiscale Geometric Analysis (MGA) tool called Ripplet Transform(RT) was proposed in the work of J.Xu, L.Yang and D.Wu. Ripplet transform is a higher dimensional generalization of curvelet transform. It provides a new tight frame with sparse representation for images with discontinuities along C_d curves. Ripplet transform generalizes curvelet transform by adding two parameters,i.e., support c and degree d. Hence, curvelet transform is just a special case of ripplet transform with c = 1 and d = 2. The new parameters provide ripplet transform with anisotropy capability of representing singularities along arbitrarily shaped curves.

The scaling done here is

$$width = c * (length)^d \tag{4.1}$$

The ripplet functions can be generated as

$$\rho_{a,\vec{b},\theta}(\vec{x}) = \rho_{a,\vec{0},0}(R_\theta(\vec{x} - \vec{b})) \tag{4.2}$$

where $\rho_{a,\vec{0},0}$ is the ripplet element function and $R_\theta = \begin{bmatrix} \cos\theta & \sin\theta \\ -\sin\theta & \cos\theta \end{bmatrix}$ is the rotation matrix.

For digital image processing discrete ripplet transform implementation is used. Scale parameter is sampled at dyadic scale, position parameter $\vec{b}$ and angle parameter θ are sampled at equal spaced interval,a,$\vec{b}$ and θ are substituted with discrete parameters $a_i, \vec{b}_k, \theta_l$

The discrete ripplet transform of MXN image $f(n_1, n_2)$ id of form

$$R_{j,\vec{k},l} = \sum_{n_1=0}^{M-1} \sum_{n_2=0}^{N-1} f(n_1, n_2)\overline{\rho_{j,\vec{k},l}(n_1, n_2)} \tag{4.3}$$

where $R_{j,\vec{k},l}$ is the ripplet coefficients

The image can be reconstructed through inverse discrete ripplet transform

$$\bar{f}(n_1, n_2) = \sum_{j} \sum_{\vec{k}} \sum_{l} R_{j,\vec{k},l}\rho_{j,\vec{k},l}(n_1, n_2) \tag{4.4}$$

4.1 Advantages

Multi-resolution : Ripplet transform provides a hierarchical representation of images. It can successively approximate images from coarse to fine resolu- tions.

Good localization : Ripplet functions have compact support in frequency do- main and decay very fast in spatial domain. So ripplet functions are well localized in both spatial and frequency domains.

High directionality : Ripplet functions orient at various directions, with the increase in resolution, ripplet functions can obtain more directions.

Anisotropy :Generalized scaling and support result in anisotropy of ripplet functions, which guarantees to capture singularities along various curves.

Chapter 5

PROPOSED METHOD

The block diagram of the proposed compression method based on Ripplet Transform is illustrated in Fig.5.1 and 5.2.The proposed method can be used for the compression of grey scale images as well as colour medical images. This method uses Ripplet Transform Type II for the compression.To further improve the quality of the compressed image, the conventional SPIHT encoder (10) is replaced by a Huffman encoder in the proposed method. In this method, colour medical image of size 256 x 256 is taken as input. The colour image is split into three bands(R,G,B).The wavelet transform is applied using biorthogonal CDF 9/7 wavelet, separately for each band. Thus, the input image is decomposed into multiresolution subbands.The low frequency subbands are directly encoded. But for the high frequency subbands, ripplet transform II is taken and then encoded. Ripplet II sub bands are directly encoded using Huffman encoding algorithm. The high frequency sub bands are dissected into small partitions by the procedure called smooth partitioning and the resulting dyadic squares are then renormalized. The effective region is analyzed in the ripplet domain.

Thus finally the resulting ripplet coefficients are further encoded using Huffman encoder. The compressed image is obtained and the compression ratio is calculated. A Huffman coding method based on Ripplet transform for compression of colour medical images is proposed.The Ripplet transform breaks the inherent limitations of wavelet transform. It represents the image in different scales and directions in order to provide high quality compressed images. Then Huffman decoding and inverse ripplet transform are taken in order to reconstruct the original image. Fig.3 shows the reconstruction part or the decompression part of the compression system. The Huffman decoding and inverse ripplet transform are taken in order to reconstruct the original image

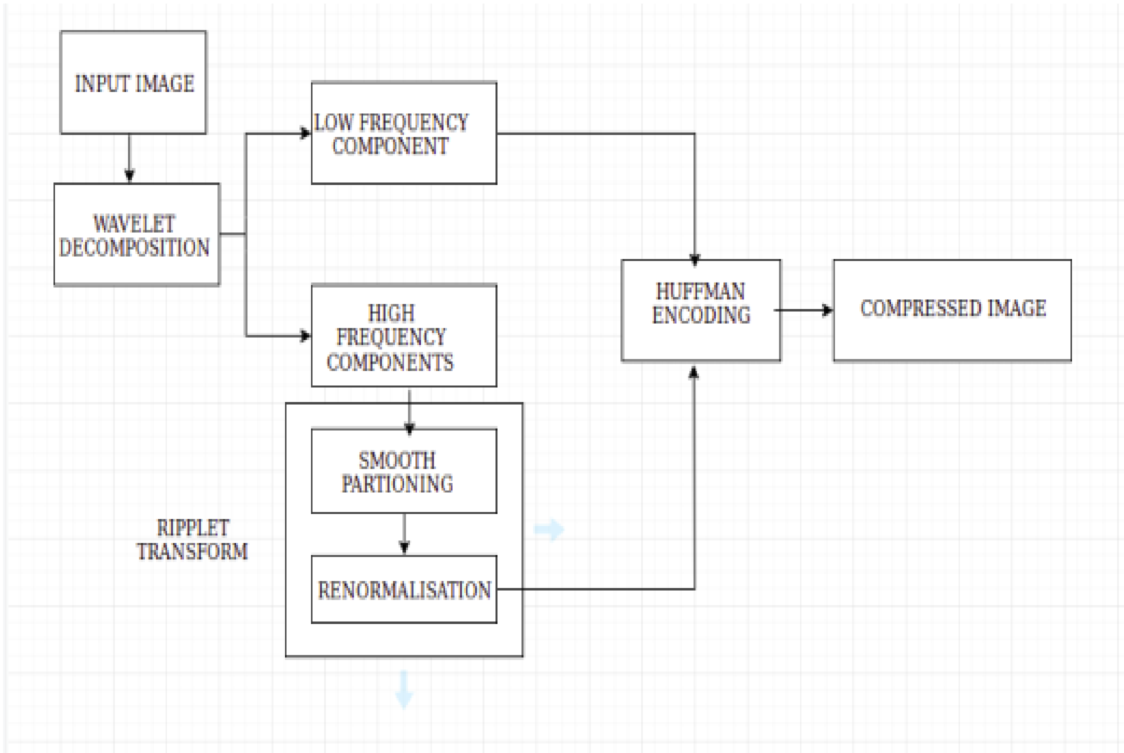

Figure 5.1: Proposed Method For Compression

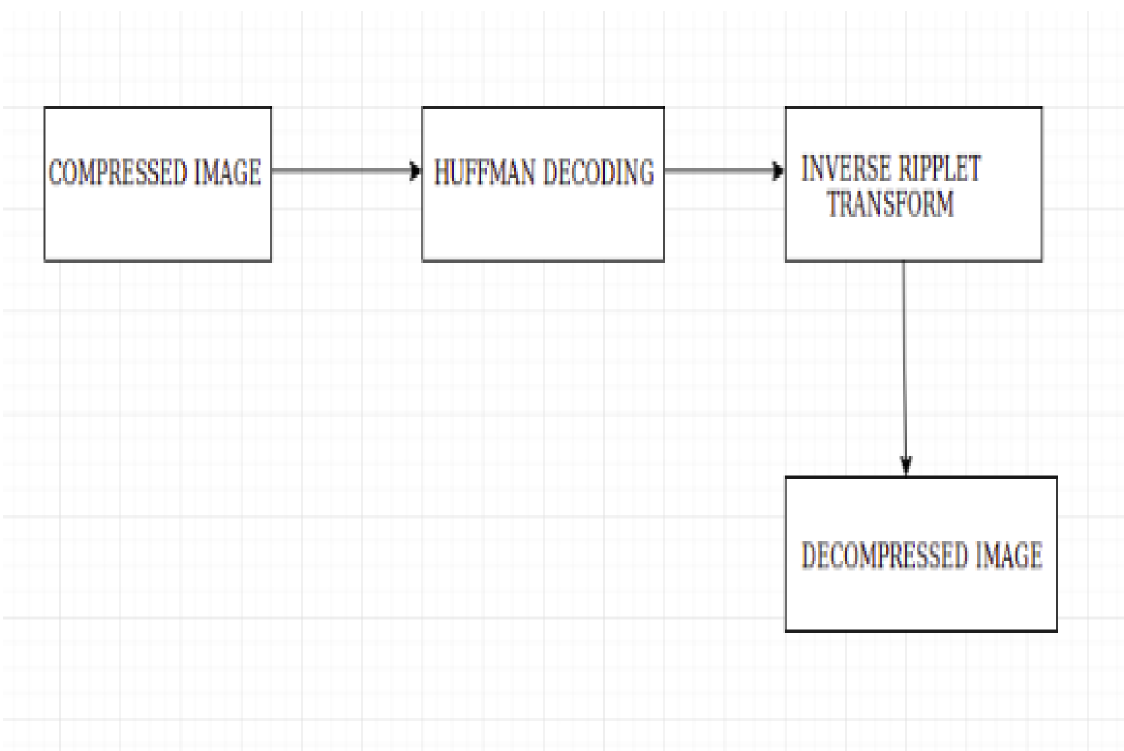

Figure 5.2: Proposed Method For Decompression

Chapter 6

SOFTWARE DESCRIPTION

6.1 MatLab

MATLAB (matrix laboratory) is a multi-paradigm numerical computing environment and proprietary programming language developed by MathWorks. MATLAB allows matrix manipulations, plotting of functions and data, implementation of algorithms, creation of user interfaces, and interfacing with programs written in other languages, including $C, C{+}{+}, C\#$, Java, Fortran and Python.

Figure 6.1: Matlab Logo

Although MATLAB is intended primarily for numerical computing, an optional toolbox uses the MuPAD symbolic engine, allowing access to symbolic computing abilities. An additional package, Simulink, adds graphical multi-domain simulation and model-based design for dynamic and embedded systems. We use matlab for the software prototyping of the compression algorithm which we developed using the Ripplet transform. MAtlab is used to verify our test results and to find the efficiency of our method.

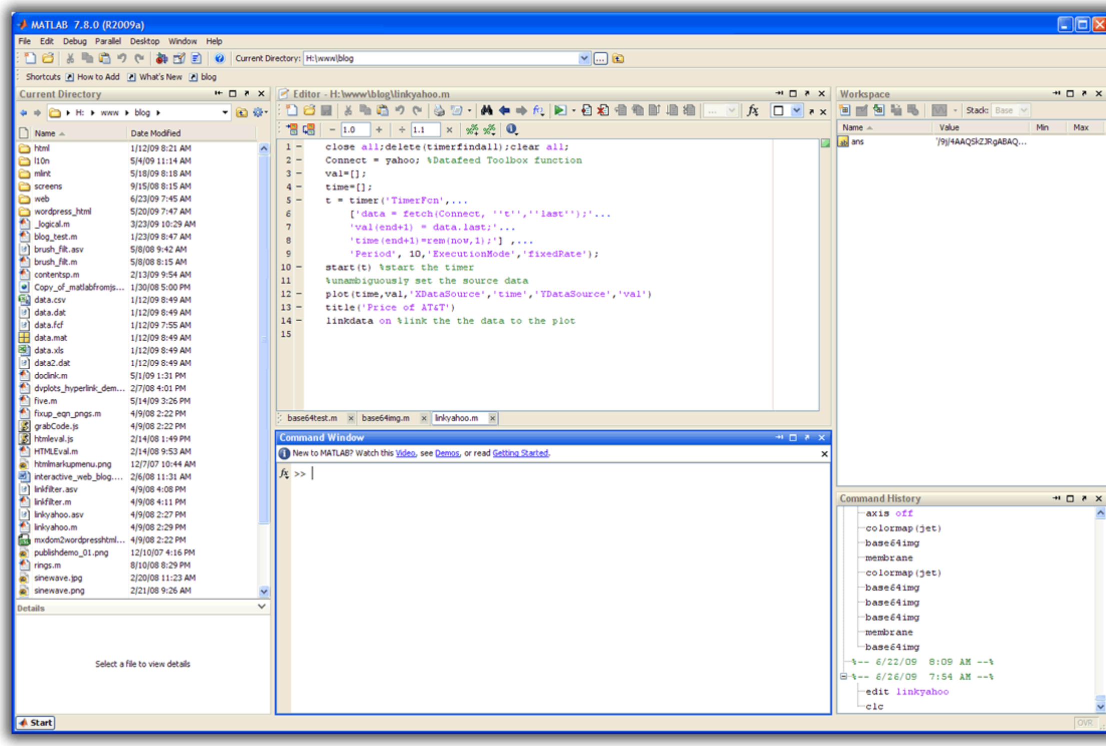

Figure 6.2: Matlab on Screen

6.2 Vivado

Vivado Design Suite is a software suite produced by Xilinx for synthesis and analysis of HDL designs, superseding Xilinx ISE with additional features for system on a chip de- velopment and high-level synthesis. Vivado represents a ground-up rewrite and re-thinking of the entire design flow (compared to ISE), and has been described by reviewers as "well conceived, tightly integrated, blazing fast, scalable, maintainable, and intuitive".

Figure 6.3: Vivado Logo

Unlike ISE which relied on ModelSim for simulation,the Vivado System Edition includes an in-built logic simulator. Vivado also introduces high-level synthesis, with a tool chain that converts C code into programmable logic. Vivado has been described as a "state-of-theart comprehensive EDA tool with all the latest bells and whistles in terms of data model, integration, algorithms, and performance". Vivado enables developers to synthesize their designs, perform timing analysis, examine RTL diagrams, simulate a design's reaction to different stimuli, and configure the target device with the programmer. Vivado is a design environment for FPGA products from Xilinx, and is tightly-coupled to the architecture of such chips, and cannot be used with FPGA products from other vendors.

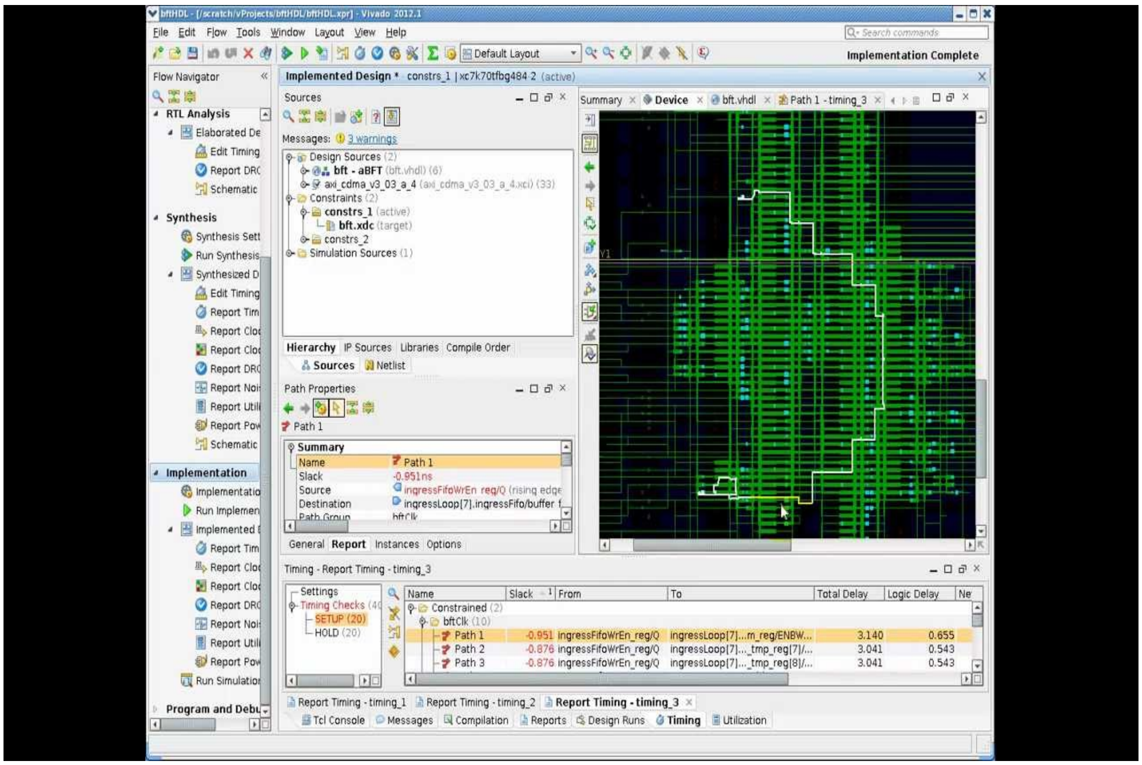

Figure 6.4: Vivado on Screen

Chapter 7

HARDWARE DESCRIPTION

The proposed hardware includes the following:

- Camera OV2640
- ESP32
- Virtex 6 (FPGA)

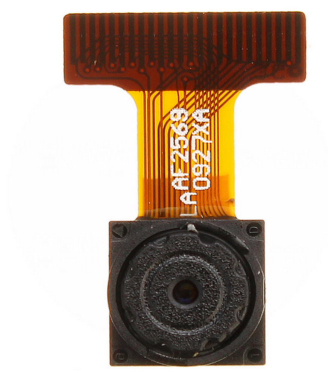

Figure 7.1: OV2640 Camera Module

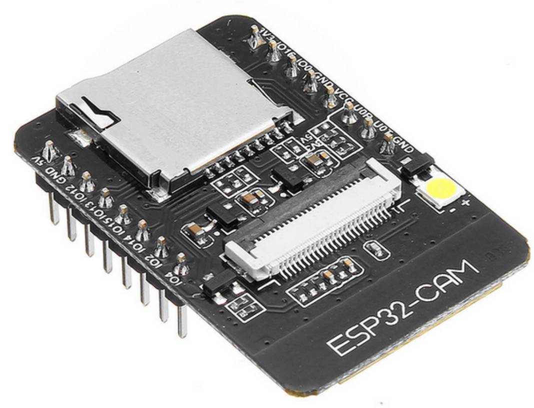

Figure 7.2: ESP-32

Figure 7.3: Virtex 6 Development Board

The basic camera module OV2640 is a low voltage CMOS sensor with 2.0 MegaPixel density.It relays real image information to ESP-32 controller with SCCB (Serial Camera Control Bus). OV2640 gives complete control over image quality, formatting and output data transfer. ESP-32 acts as an interface between camera and FGPA. Image data is sent to the FPGA from ESP-32 serially. Received data is processed in the FPGA using the above proposed algorithm and compressed data is created. This data is then fed to a computer serially and analyzed for efficiency.

Chapter 8

TESTING PARAMETERS

8.1 Peak Signal To Noise Ratio (PSNR)

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.

$$PSNR = 20 \log_{10} \frac{n255}{||x - y||} \tag{8.1}$$

8.2 Compression Ratio(CR)

compression ratio is the amount of bits in the original image divided by the amount of bits in the compressed image.

$$CR = \frac{Size\,of\ original\ image}{Size\,of\ compressed\,image} \tag{8.2}$$

8.3 Mean Square Error(MSE)

The mean squared error (MSE) measures the average of the squares of the errors—that is, the average squared difference between the estimated values and what is estimated.

$$MSE = \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} (f(i,j) - f'(i,j))^2 \tag{8.3}$$

8.4 Bit rate

Bit rate is the number of bits that are conveyed or processed per unit of time

$$Bit\ rate = \frac{Compressed\ image\ size\ in\ bits}{total\ number\ of\ pixels} \tag{8.4}$$

Chapter 9

IMPLEMENTATION

9.1 MatLab Verification

A common test image, Barbara in jpeg format with a size of 100kB was converted into wavelet domain using Biorthogonal filter. Level decomposition provided the horizontal level, vertical level, diagonal level and approximation of the given image.

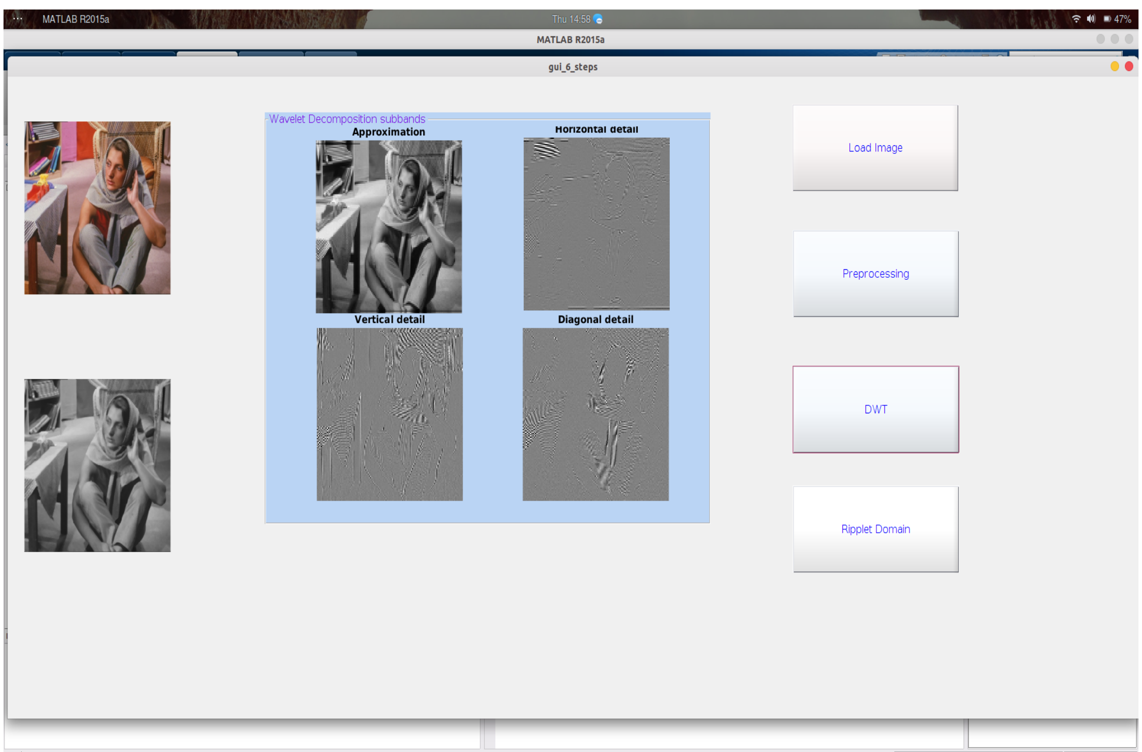

Figure 9.1: Feature extraction

The diagonal level of this approximation gives us the high frequency component of the image Ripplet transformation is performed there. For that we need to perform smooth partitioning and re-normalization on the wavelet part of high frequency component to convert into the frequency domain.

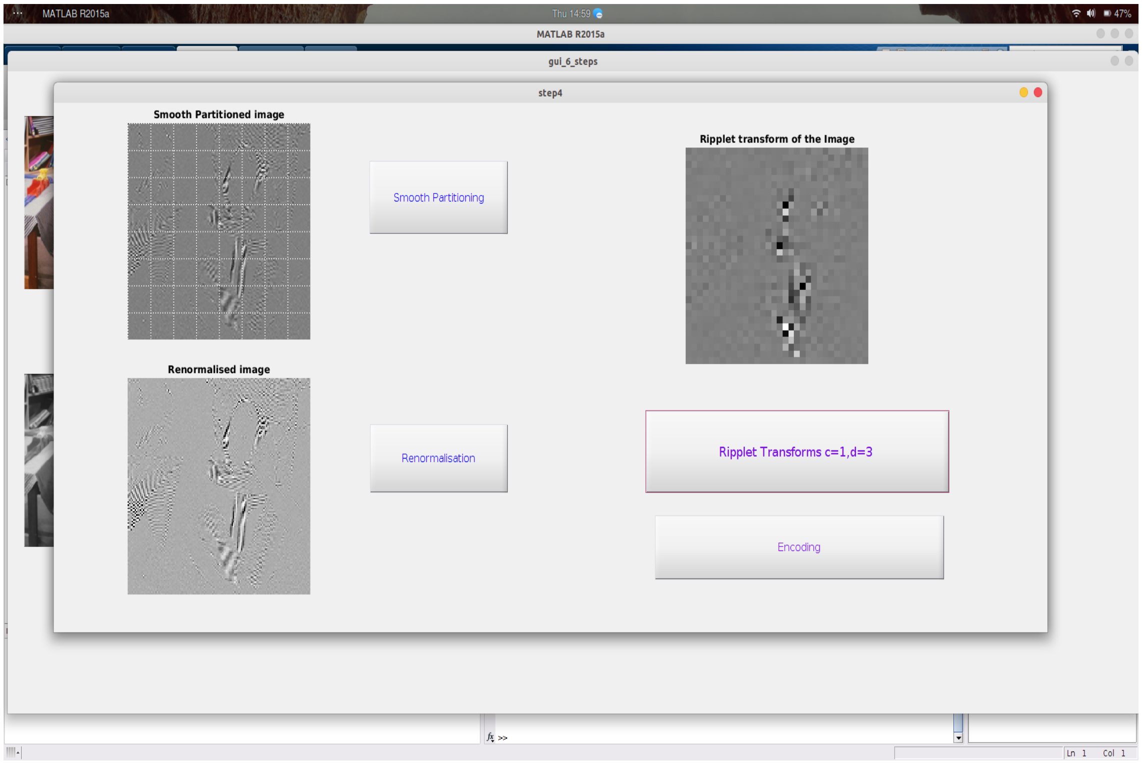

Figure 9.2: Ripplet Transform on the high frequency component

After analysis different coding algorithms it was found that huffman code to perform better among the other candidates. Huffman coding is a variable length coding technique that can decrease the size of a bits stream corresponding to a predefined dictionary. This library is based on the differential entropy of the input image.

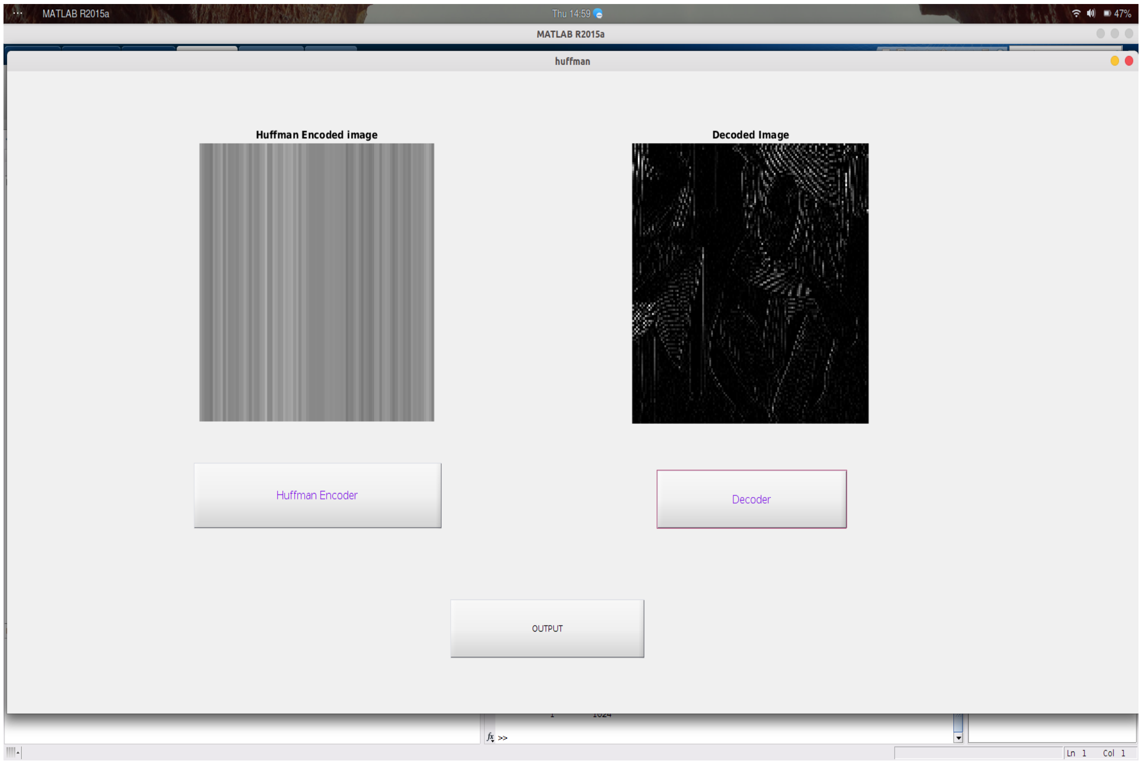

Figure 9.3: Huffman Encoding and Decoding

The reverse operation were performed to decompress the image.

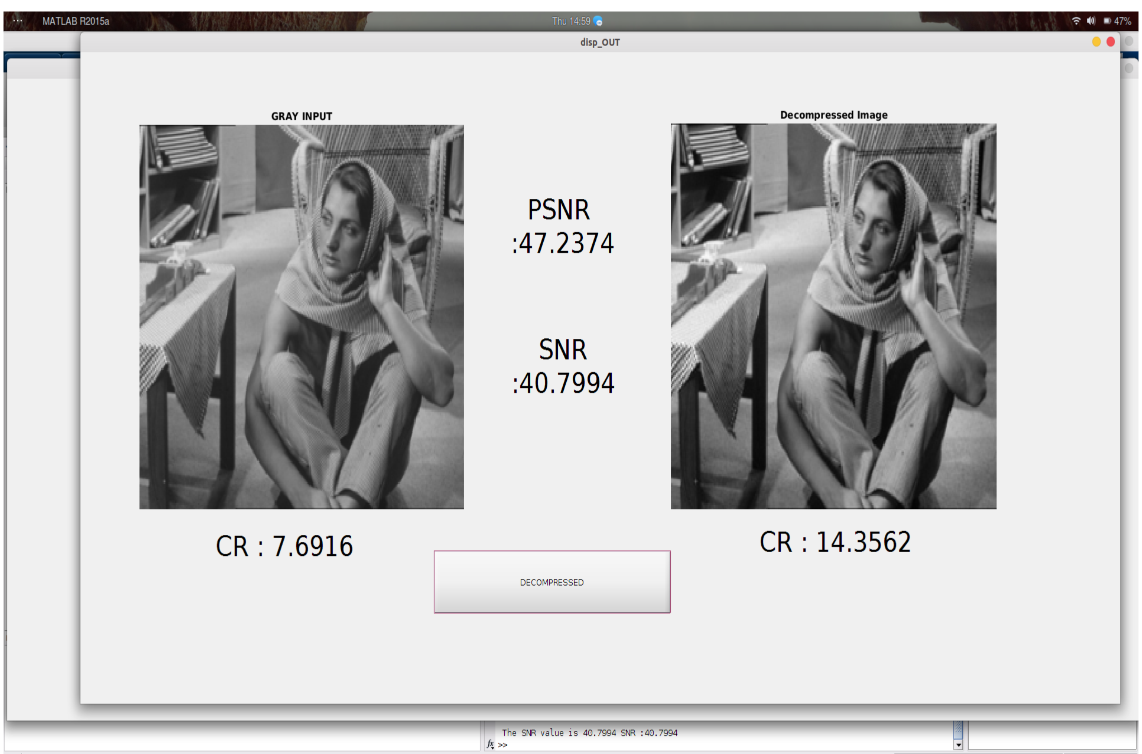

Figure 9.4: Final results

9.2 Using Vivado for FPGA

The basic implementation of the project can be divided into 3 parts ,first there is the i/o part where serial communication protocol can be used to input the data serially bit by bit. Data which is received should be stored in memory module which we code,we could use a DDR3 memory module to store the bit wise data, the stored data is then run through our compression algorithm, which is written with the help of the Vivado ipcores,the algorithm is written using verilog.with the help of the fpga we can test the feasibility of the hardware implementation of the algorithm we developed.

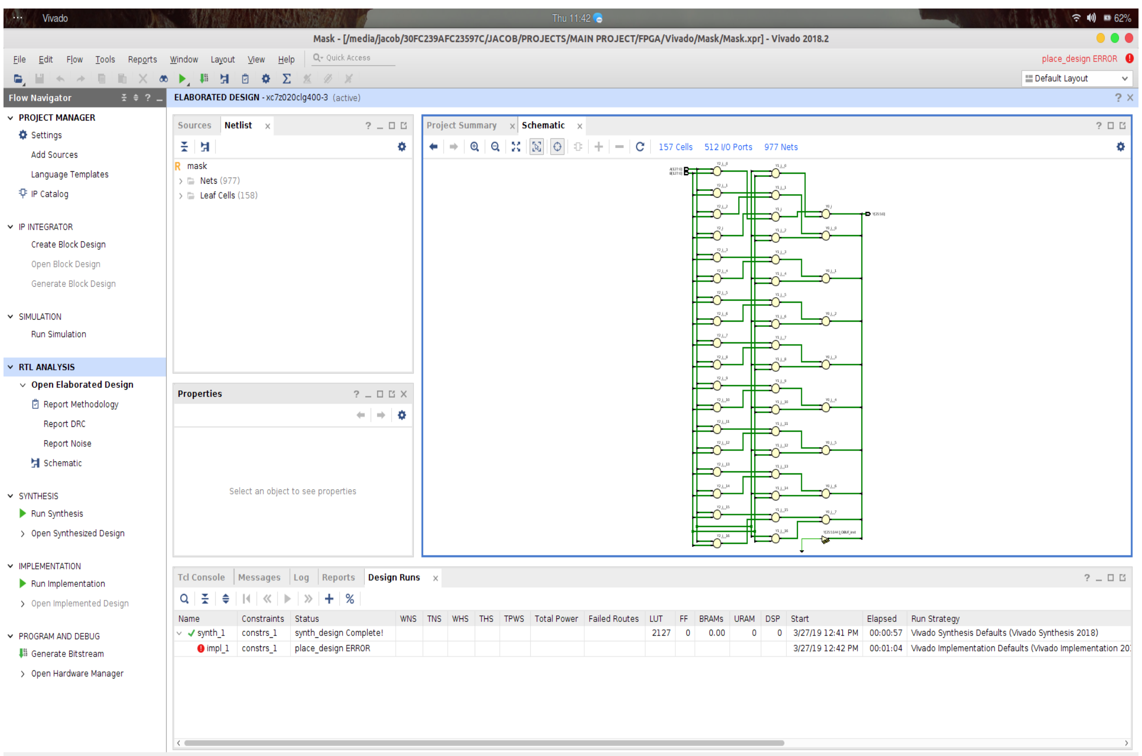

Figure 9.5: Basic mask RTL design in Vivado

Chapter 10

RESULTS

We selected different test images to check whether our algorithm is working correctly. The test images we took include barbara, baboon,einstein,crowd and self taken picture of a man and a camera shutter.

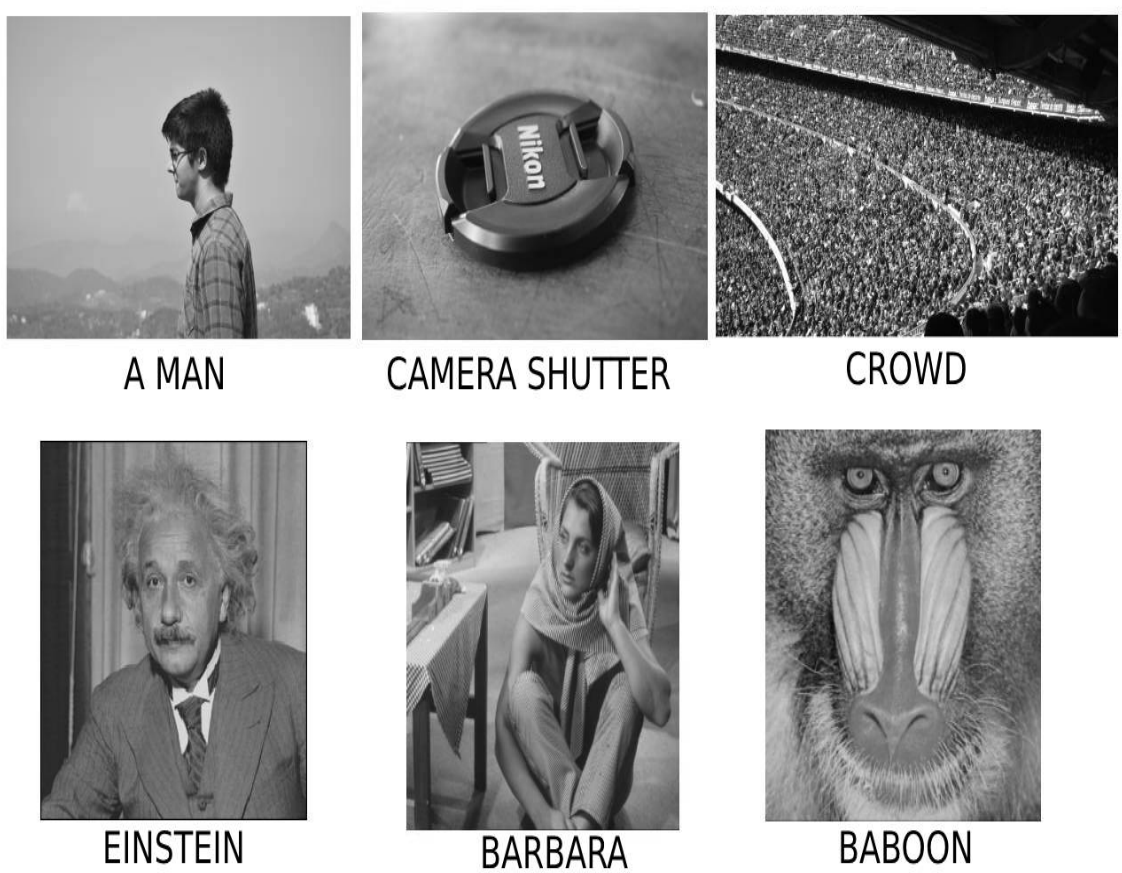

Figure 10.1: Test images

A summerized table in the fig 10.1 shows the final results we obtained.

Image	PSNR	SNR	CR	MSE	Bit rate
Barbara	47.2374	40.7994	14.3562	0.14699	039003
Baboon	38.4293	32.8144	10.3745	0.27716	0.62787
Enstein	45.3202	38.3262	16.3187	0.24893	0.4985
A man	61.7133	58.2233	32.2044	0.41732	.32656
Crowd	33.0507	25.0274	8.1736	1.5726	0.37313
Cmaera shutter	54.8817	49.0477	22.1082	0.39441	3.0002

Figure 10.2: Analysis results

We were able to find that the compression ratio of all images improved. This is shown in the fig 10.2.Similarly from the fig 10.3 we can see that the PSNR ans SNR values shows good quality image.Fig 10.3 and 10.4 gives the different MSE and bit rate value value we obtained for the test images.

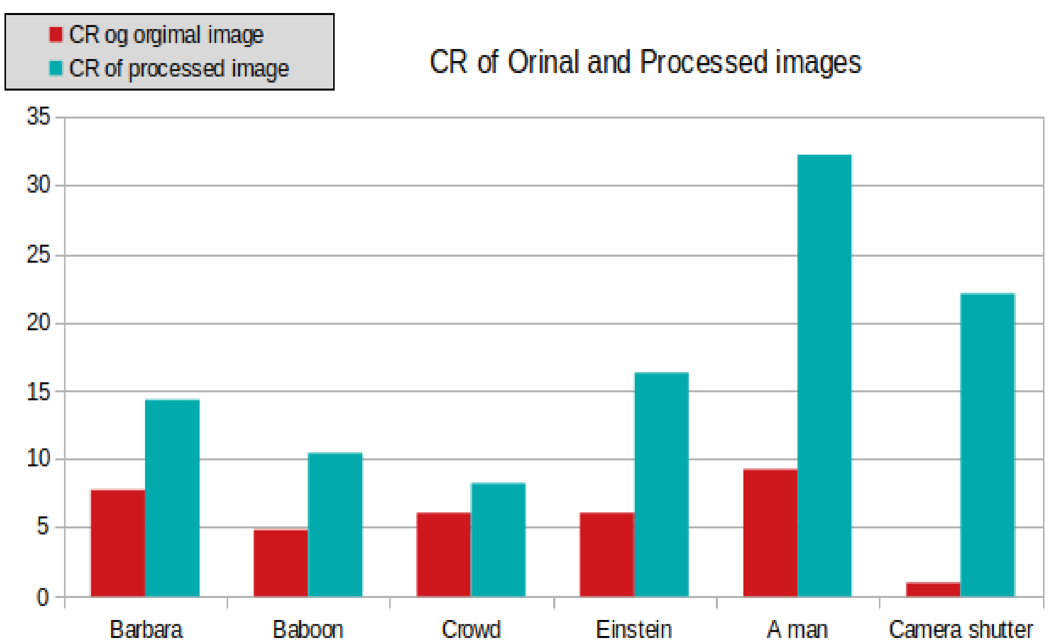

Figure 10.3: Compression ratio of test image

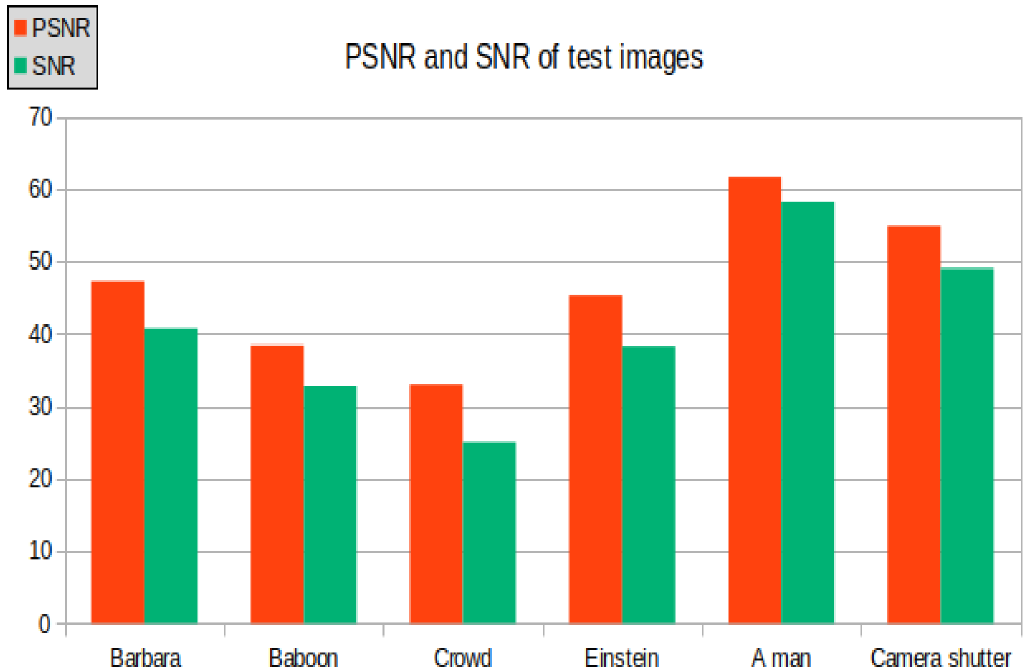

Figure 10.4: PSNR and SNR of test image

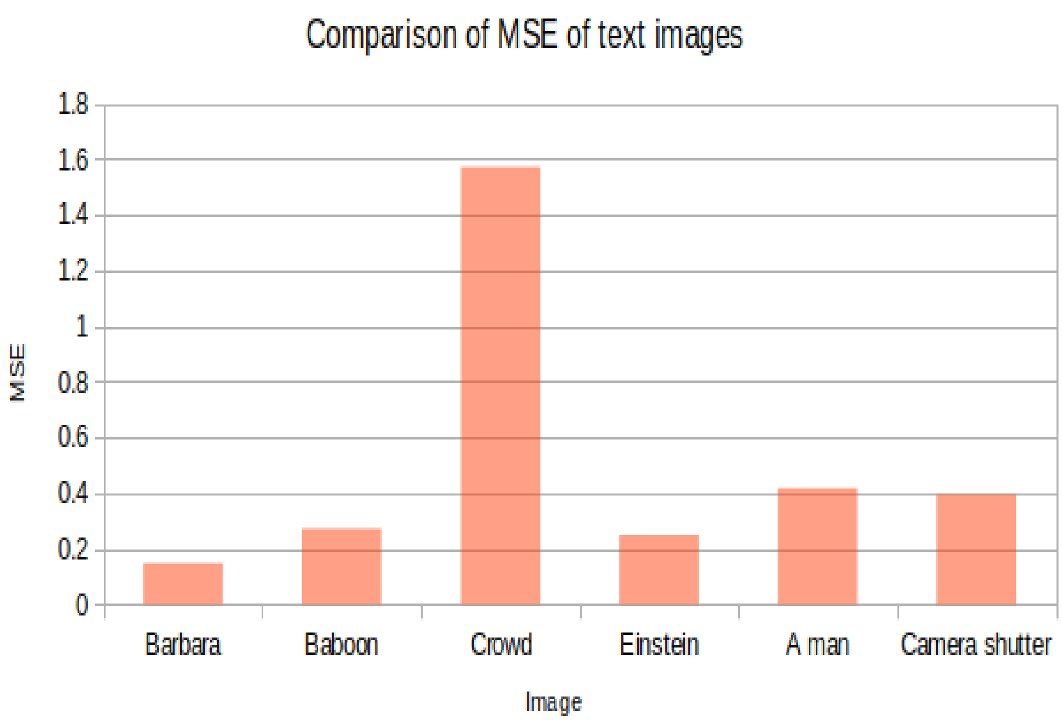

Figure 10.5: MSE of test images

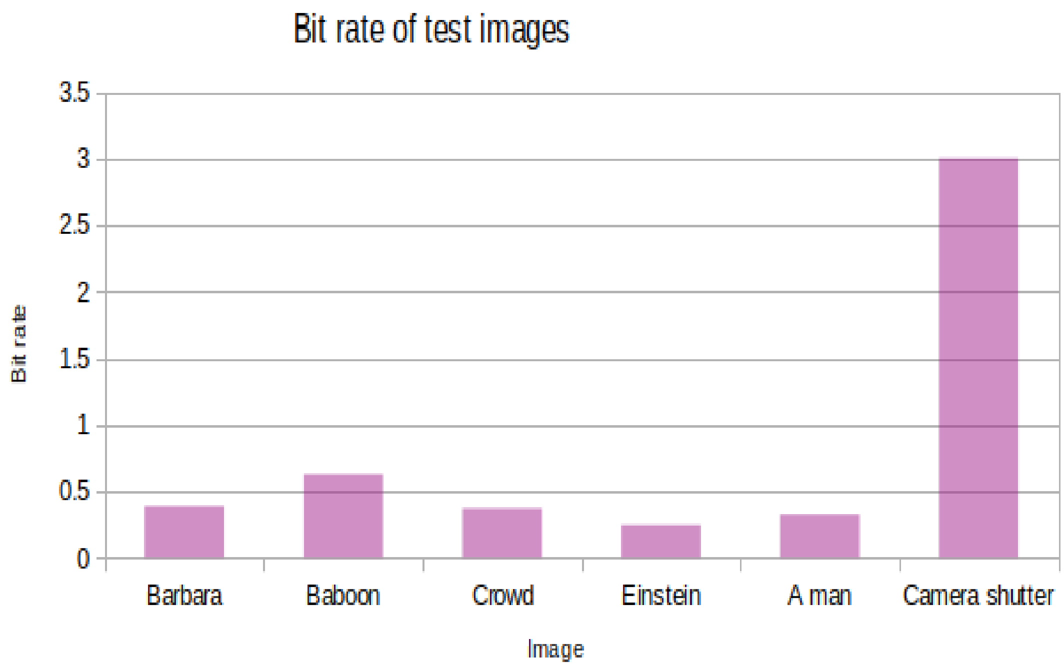

Figure 10.6: Bit rate of test image

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