Abstract **- Images are now an important part of our lives. It is used in different domains.This increases the difficulties for a orage 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.**

key words **- Image compression,ripplet transform, Huffman algorithm, compression ratio, signal to noise ratio, peak signal to noise ratio.**

I. INTRODUCTION

From early days to now, the basic objective of image compression is the reduction of size forstorage 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 subimages. 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.

II. REVIEW OF LITERATURE

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.

III. 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 representation 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

$$width = c * (length)^d \tag{1}$$

The ripplet functions can be generated as

$$\rho_{a,\vec{b},\theta}(\vec{x}) = \rho_{a,\vec{0},0}(R_\theta(\vec{x} - \vec{b})) \tag{2}$$

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

$$R_{j,\vec{k},l} = \sum_{n_1=0}^{M-1} \sum_{n_2=0}^{N-1} f(n_1, n_2) \overline{\rho_{j,\vec{k},l}(n_1, n_2)} \tag{3}$$

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

The image can be reconstructed through inverse discrete ripplet transform

$$\bar{f}(n_1, n_2) = \sum_{j} \sum_{\vec{k}} \sum_{l} R_{j,\vec{k},l} \rho_{j,\vec{k},l}(n_1, n_2) \tag{4}$$

Advantages of this transform include:

- 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.

IV. PROPOSED METHOD

The block diagram of the proposed compression method based on Ripplet Transform is illustrated in Fig.2.The proposed method can be used for the compression of grey scale medical 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.

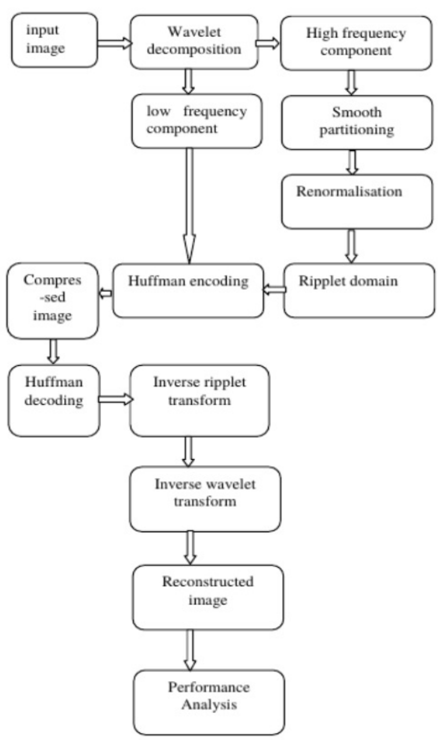

Figure 1: Proposed Method

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

V. RESULT

Initially we selected a common test image. We chose Barbara in jpeg format with a size of 100kB.Then we performed converted the image into wavelet domain using Biorthogonal 3.7 filter. We performed two level decomposition and thus obtained horizontal level 1 and 2, vertical level 1 and 2, diagonal level 1 and 2 and approximation of the given image. In this approximation gives us the low frequency component and remaining gives us the high frequency component.

(2).png

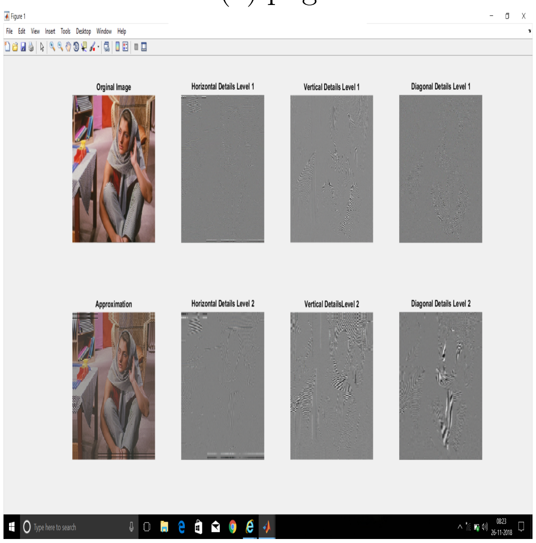

Figure 2: Feature extraction from image

Then applied wavelet compression on the all the features extracted. Using inverse wavelet transform we re-synthesized the image with high quality. We were able to reconstruct the image without any significant difference from the original image.

We obtained the following results:

- Compression ratio of 17.5
- PSNR Value of 47.45
- SNR of 41.46

We need to perform ripplet transformation to high frequency domain. for that we need to perform smooth partitioning and re-normalization on the wavelet part of high frequency component.In that part we developed code for re normalisation.

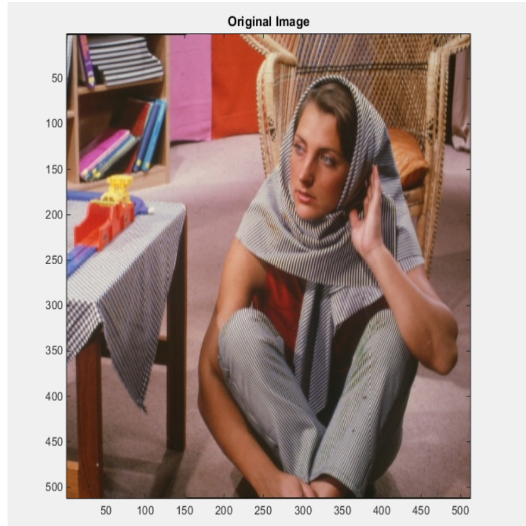

Figure 3: Orginal image(size100kB)

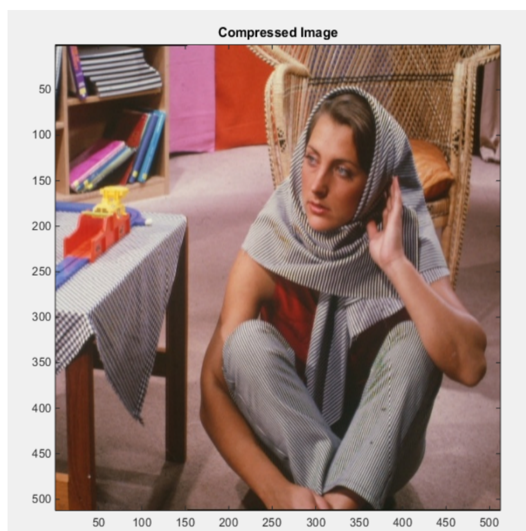

Figure 4: Compressed image(size 44KB)

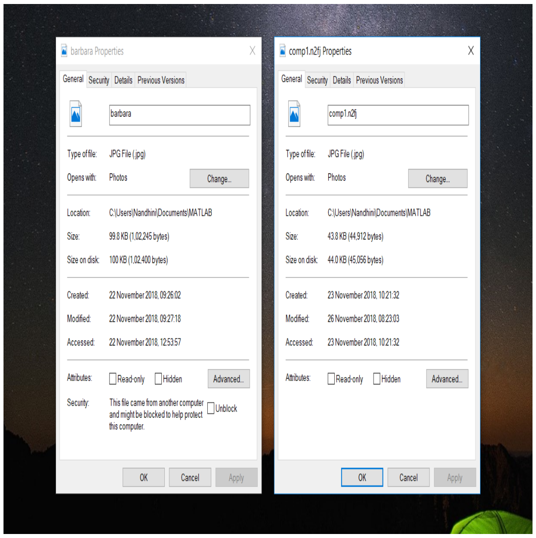

Figure 5: Comparison of size

Figure 6: Output of Huffman coding

We performed analysis on different coding algorithms and found huffman code to perform better among the better candidates. Huffman coding is a variable length coding technique that can decrease the size of a bitstream corresponding to a predefined dictionary. This library is based on the differential entropy of the input image. We Implemented the min-Heap

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