CHAPTER 5

IMAGE COMPRESSION

5.1 INTRODUCTION

The objective of image compression is to reduce irrelevance and redundancy of the image data in order to store or transmit data in an efficient form. Image Compression is widely addressed in research areas. Numerous compression standards have been in place, but still there is a scope for higher compression with quality reconstruction. Lossless compression refers to compression techniques in which the reconstructed data exactly matches the original. Lossy compression denotes compression methods, which gives 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. Both lossless and lossy compression find potential applications in remote sensing, medical, 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, lossy compression becomes a feasible solution, as on the one hand, it provides significantly higher compression gains 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 compression 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. Some 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 dropping the overall bandwidth requirements. In fact, the new still image compression standard, JPEG 2000, provides such features in its extended form. In other words, the proposed technique produces a bit stream that result in a progressive reconstruction of the image.

Image Compression is the process of converting an input data stream into an output stream with smaller size. It is performed by removing the redundant or repeated bits in a pixel. Basically, compression may be used where the memory size of the images is limited to certain bytes or kilobytes.

The compression technique is based on the following principle

- Reducing the number of bytes required to represent the digital image
- Reducing the patterns
- The uncorrelated data confirms the redundant data elimination.

Compresssion Model: The basic compression model is given in the Figure 5.1. It consists of Encoding, Transmission and Decoding. In the Encoding process, the input image is sent to the Source Encoder which removes redundancies in the pixel and then it is passed through Channel Encoder which ensures robustness against noise. Now, the Encoded image is
transmitted through the channel, and the receiver side, the decoding process is done using the Channel decoder and Source Decoder.

Figure 5.1 Compression model

Compression Types: Basically, the compression is of two types. They are Lossy compression and Lossless compression.

Lossy Compression: In general, the lossy compression means that there will be loss in the quality of the images. This small amount of loss in the quality of image is called lossy compression. It is most commonly used to compress multimedia data such as audio, video, and still images, especially in applications as media and internet telephony. Because the loss in this type of the images are said to be inconsiderable. More generally, lossy compression can be thought of as an application of transform coding in the case of multimedia data, perceptual coding transforms the raw data to a domain which more accurately reflects the information content.

Data reduction is the main goal of transform coding, it also allows other goals. One may represent data more accurately for the original amount of space. This is because uncompressed audio can only reduce file size by lowering bit rate or depth, whereas compressing audio can reduce size while maintaining bit rate and depth. Further, a transform coding may provide a better domain for manipulating or otherwise editing the data. From this point of view, perceptual encoding is not essentially about discarding data, but rather about a improved representation of data.
Lossless Compression: By contrast, lossless compression is required for text and data files, such as bank records and text articles. In many cases, it is advantageous to make a master lossless file that can then be used to produce compressed files for different purposes. Lossless compression is preferred for archival purposes and often for medical imaging, technical drawings, clipart, or comics. This is because lossy compression methods, especially when used at low bit rates, introduce compression artefacts. Lossy methods are especially suitable for natural images such as photographs in applications where minor sometimes imperceptible loss of fidelity is acceptable to achieve a substantial reduction in bit rate. The lossy compression that produces imperceptible differences may be called visually lossless.

In order to analyse the efficient transform among the transforms used for compression, three parameters such as Compression Ratio (CR), Mean Square Error (MSE) and Peak Signal to Noise Ratio (PSNR) can be calculated by using the following formulae.

**Compression Ratio (CR)**: It is the ratio of size of input image to the size of output image. Compression Ratio defined by using the equation (5.1)

\[
CR = \text{Size of Input Image} / \text{Size of Output Image}
\]  

(5.1)

**Root Mean Square Error (RMSE)**: It is the estimation as of one of the many values to quantify the difference between the inputs. Root Mean Square Error can be defined by using the equation (5.2)

\[
\text{RMSE} = \sqrt{\frac{1}{NM} \sum_{x=0}^{N-1} \sum_{y=0}^{M-1} f(x,y) - f^*(x,y)}
\]  

(5.2)
Where $f(x, y)$ is the original image data and $f^R(x, y)$ is the compressed image value, $M$ and $N$ are the dimensions of the images. $M$ represents the numbers of rows of pixels of the images and $N$ represents the number of columns of pixels of the image.

**Peak Signal to Noise Ratio (PSNR)** The PSNR of the fusion result is defined by using the equation (5.3)

$$\text{PSNR} = 10 \times \log \left( \frac{(f_{\text{max}})^2}{\text{RMSE}^2} \right) \quad (5.3)$$

Where $f_{\text{max}}$ is the maximum gray scale value of the pixels in the image.

5.2 IMAGE COMPRESSION USING TRANSFORMS

The Ridgelet Transform, Curvelet Transform and Contourlet Transform like the wavelet transform, is a multiscale transform, with frame elements indexed by scale and location parameters. Unlike the wavelet transform, it has directional parameters, and the curvelet pyramid contains elements with a very high degree of directional specificity. In addition, the Curvelet transform is based on a certain anisotropic scaling principle which is quite different from the isotropic scaling of wavelets. The elements obey a special scaling law, where the length of the support of a frame elements and the width of the support are linked by the relation width $\frac{1}{4}$ length$^2$. All of these properties are very stimulating and have already lead to a range of interesting idealized applications, for example in tomography and in scientific computation.

**Proposed Algorithm:** The following algorithm performs the compression process.
STEP1: Initialization

The input image is read from the user and it is resized to 256*256 image.

STEP2: 3-level decomposition

Next step is the process of decomposition, where three level decomposition is done. In the first level of decomposition, the resized 256*256 image is decomposed into an image of size 128*128. In the second level decomposition, it is further decomposed into an image of size 64*64. In the third level decomposition, it is decomposed into an image of size 32*32.

STEP3: Quantization

After the decomposition process of quantization, the co-efficients in each sub-band are scalar quantized i.e., the pixel values are rounded off to the nearest integer value. Quantization step size is based on the dynamic range of the sub-band values and constants.

STEP4: Thresholding

Next step is thresholding. First a threshold value is set. Then, the pixel values below the threshold value are made zero and the pixel values above the threshold value are retained. The threshold value is chosen depending upon the size of the input image. Since resize all the input images to an image of size 256*256, the threshold value 1 is chosen.

STEP5: Finding the co-efficients

Next step is to find the corresponding co-efficients.
STEP 6: Reconstruction and computing the parameters

Finally the original image is reconstructed and the parameters such as CR, PSNR and MSE are calculated.

5.3 WAVELET TRANSFORM

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

The Fourier transform is a tool widely used for many scientific purposes, but it is well suited only at the study of stationary signals where all frequencies have an infinite coherence time. The analysis brings only global information which is not sufficient to detect compact patterns. Gabor introduced a local Fourier analysis, taking into account a sliding window, leading to a time frequency-analysis. This method is only applicable to situations where the consistency analysis is independent of the frequency. This is the case for instance for signals which have their coherence time determined by the geometry of the oral cavity. Morlet introduced the Wavelet Transform in order to maintain a coherence time proportional to the period.

The wavelet transform is computed separately for different segments of the time-domain signal at different frequencies. Multi-resolution analysis analyzes the signal at different frequencies giving different resolutions. MRA is designed to give good time resolution and poor
frequency resolution at high frequencies and good frequency resolution and poor time resolution at low frequencies. Good for signal having high frequency components for short durations and low frequency components for long duration e.g. images and video frames. Wavelets are mathematical functions defined over a finite interval and having an average value of zero that transform data into different frequency components, representing each component with a resolution matched to its scale.

The basic idea of the wavelet transform is to represent any arbitrary function as a superposition of a set of such wavelets or basis functions. These basis functions or baby wavelets are obtained from a single prototype wavelet called the mother wavelet, by dilations or contractions (scaling) and translations (shifts). Many new wavelet applications such as image compression, human vision, radar, and earthquake prediction are developed in recent years. In wavelet transform the basis functions are wavelets. Wavelets tend to be irregular and symmetric. All wavelet functions, \( w(2kt - m) \), are derived from a single mother wavelet \( w(t) \). This wavelet is a small wave or like pulse which is shown in Figure 5.2

\[ \text{Figure 5.2 Mother wavelet } w(t) \]

The wavelets are called orthogonal when their inner products are zero. The smaller the scaling factor is, the wider the wavelet is. Wide wavelets are comparable to low frequency sinusoids and narrow wavelets are comparable to high frequency sinusoids.
Wavelet analysis produces a time scale view of a signal. Scaling a wavelet simply means stretching (or compressing) it. The scale factor is used to express the compression of wavelets and often denoted by the letter a. The smaller the scale factor, the more compressed the wavelet. The scale is inversely related to the frequency of the signal in wavelet analysis.

Shifting a wavelet simply means delaying (or hastening) its onset. Mathematically, delaying a function \( \Psi(t) \) by \( k \) is represented by \( \Psi(t-k) \) and the schematic is shown in Figure 5.3.

![Wavelet function \( \Psi(t) \) and shifted wavelet function \( \Psi(t-k) \)](image)

**Figure 5.3 Shifted wavelets**

The higher scales correspond to the most stretched wavelets. In the more stretched the wavelet, the longer the portion of the signal with which it is being compared, and thus the coarser the signal features being measured by the wavelet coefficients. The relation between the scale and the frequency is shown in Figure 5.4.

![Wavelet signal and wavelet](image)

**Figure 5.4 Scale and frequency**
Thus, there is a correspondence between wavelet scales and frequency as revealed by wavelet analysis.

Low Scale

- Compressed wavelet
- Rapidly changing details
- High frequency.

High Scale

- Stretched wavelet
- Slowly changing, coarse features
- Low frequency.

When analyze the signal in time for its frequency content, unlike Fourier analysis, which analyze signals using sine and cosine, now use wavelet functions.

- Provides time-frequency representation
- Wavelet transform decomposes a signal into a set of basis functions (wavelets)
- Wavelets are obtained from a single prototype wavelet \( \Psi(t) \) called mother wavelet by dilations and shifting.

In numerical analysis and functional analysis, a Discrete Wavelet Transform (DWT) is any wavelet transform for which the wavelets are discretely sampled. As with other wavelet transforms, a key advantage of Fourier transforms is temporal resolution i.e. it captures both frequency and location information (location in time).
The DWT of a signal $x$ is calculated by passing it through a series of filters. First the samples are passed through a low pass filter with impulse response resulting in a convolution. The signal is also simultaneously decomposed using a high pass filter. The output gives the detail coefficients from the high-pass filter and approximation coefficients from the low-pass. It is important that the two filters are related to each other and they are known as a Quadrature Median Filter (QMF). However, since half the frequency of the signal has now been removed, half the samples can be discarded according to Nyquist’s rule. The filter outputs are then sub sampled by 2 (Mallat’s and the common notation is the opposite, $g$ - high pass and $h$ - low pass).

\[
y_{\text{low}}[n] = \sum_{k=0}^{n} x[k]g[2n-k]
\]

\[
y_{\text{high}}[n] = \sum_{k=0}^{n} x[k]h[2n+1-k]
\]

where $x(k)$ - Input Sample

$g(n-k)$ - Shifted Impulse Response (low Pass)

$h(n-k)$ - Shifted Impulse Response (high Pass)

This decomposition has halved the time resolution and half of each filter output characterizes the signal. However, each output has half the frequency band of the input so the frequency resolution has been doubled.

**Properties:** The Haar DWT illustrates the desirable properties of wavelets in general. First, it can be performed in $O(n)$ operations. Then, it captures not only a notion of the frequency content of the input, by examining it at different scales, but also temporal content, i.e. the times at which these frequencies occur. Combined, these two properties make the Fast wavelet transform (FWT) an alternative to the conventional Fast Fourier Transform (FFT).
The 2-D sub-band decomposition is just an extension of 1-D sub-band decomposition. The entire process is carried out by executing 1-D sub-band decomposition twice, first in one direction (horizontal), then in the orthogonal (vertical) direction. For example, the low-pass sub-bands (Li) resulting from the horizontal direction is further decomposed in the vertical direction, leading to LL1 and LH1 sub-bands. Similarly, the high pass sub-band (Hi) is further decomposed into HLi and HHi. After one level of transform, the image can be further decomposed by applying the 2-D sub-band decomposition to the existing LL1 sub-band. This iterative process results in multiple transform Levels.

<table>
<thead>
<tr>
<th>LL1</th>
<th>HL1</th>
<th>HL2</th>
<th>HL3</th>
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</thead>
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<tr>
<td>LH1</td>
<td>HH1</td>
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<td></td>
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<tr>
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</tr>
<tr>
<td>LH3</td>
<td></td>
<td>HHi</td>
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</tr>
</tbody>
</table>

**Figure 5.5 3-level decomposition**

In Figure 5.5 the first level of transform results in LH1, HL1, and HH1, in addition to LL1, which is further decomposed into LH2, HL2, HH2, LL2 at the second level, and the information of LL2 is used for the third level transform. The sub-band LL1 is a low-resolution sub-band and high-pass sub-bands LH1, HL1, HH1 are horizontal, vertical, and diagonal sub-band respectively since they represent the horizontal, vertical, and diagonal residual information of the original image.

### 5.3.1 Performance Evaluation

The proposed algorithm for the compression of MRI and CT images is tested with MedPix™ database and real time database images. For the evaluation of the performance of the compression algorithms, the visual quality of the obtained compression result as well as the quantitative analysis
are used. The transforms namely Wavelet Transform, Ridgelet Transform, Curvelet Transform and Contourlet Transform are applied using MATLAB simulation software. Comparison is made using the parameters such as Compression Ratio (CR), RMSE and PSNR (as earlier discussion in equation (5.1), (5.2) and (5.3)).

**Simulation Results**: Figure 5.6 shows that Input Image, Denoised Image, Quantized Image, Thresholded Image and Compressed output Image using wavelet transform.
Figure 5.6 Simulation results for Medical Image CT using WT
5.4 RIDGELET TRANSFORM

Ridgelet analysis was developed by Candès and Donoho (1999) for solving important problems such as constructing neural networks or approximating and estimating multivariate functions by linear combinations of ridge functions. Ridgelet transform is a new multiscale representation for functions on continuous spaces that have some discontinuities along lines. Orthonormal version of the ridgelet transform for discrete and finite-size images was proposed by Minh Do and Vetterli (2005). It uses the finite Radon transform as a basic building block. This leads to a set of directional and Orthonormal bases for images.

Ridgelet transform is the advanced compression technique in the field of image compression which has more advantages as compared with the other previously evolved transforms such as wavelet transform, curvelet transform, and contourlet transform. The ridgelet transform is mainly used for compressing the images that contain more number of twists and turns.

The main advantage of using Ridgelet transform is that the signal to noise ratio and the mean square error of the compressed image is lesser as compared with other transforms such as wavelet transform, curvelet transform, and contourlet transform. In Ridgelet transform, the memory size of the image is reduced without affecting the quality of the image and also the reconstruction of the original image from the compressed image can be done easily.

The continuous ridgelet transform of an integrable bivariate function $f(x)$ is represented by the equation (5.6) given below

$$\text{CRT}(a,b,\theta) = \int_{\mathbb{R}^2} \Psi_{a,b,\theta}(x)f(x)d$$

(5.6)
Where ridgelets \( \psi_{a,b,\theta}(x) \) in 2-D, are defined from a wavelet type function in 1-D \( \psi(x) \) as represented by the equation (5.7)

\[
\psi_{a,b,\theta}(x) = a^{-1/2} \psi((x \cos \theta - y \sin \theta - b)/a)
\]  

(5.7)

where \((x,y)\), \(R\) is a real number, \((a, b)\) are function of two variables which is obtained as a scalar function and \(\theta\) is the angle of orientation.

Wavelets are good to represent the point singularities and ridgelets represent line singularities. In Image Processing applications it is important to detect singularities along edges. Ridgelets can be thought of a way of juxtaposing 1-D wavelets along lines. This results in a very effective representation of objects with singularities along lines. In 2-D, points and lines are related through the Radon transform (Anderson et al 2000 and Vetterli et al 2005), thus the wavelet and ridgelet transforms are linked through the Radon transform. It is denoted as given in the equation (5.8)

\[
R_t(\theta, t) = \int_{\mathbb{R}^2} f(x,y) \delta((x \cos \theta + y \sin \theta - t) dx dy
\]  

(5.8)

where \(R\) denotes the real line.

The relationship between the Ridgelet transform and the Radon transform is shown in the Figure 5.7.

![Figure 5.7 Relation between transforms](image)
**Simulation Results:** Figure 5.8 shows that Input Image, Denoised Image, Quantized Image, Thresholded Image and Compressed output Image Ridgelet transform.

![Simulation Results Images](image)

(a) Input Image  
(b) Decomposed Image

(c) Quantized Image  
(d) Thresholded Image

(e) Output Image

*Figure 5.8 Simulation results for Medical Image CT using RT*
Medical Image - MRI - BRAIN 1

<table>
<thead>
<tr>
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<th>Ridgelet</th>
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<tbody>
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<tr>
<td>PSNR (dB)</td>
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<td>RMSE</td>
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Medical Image - MRI - BRAIN MRI ABCESS

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<tr>
<td>RMSE</td>
<td>2.8849</td>
</tr>
</tbody>
</table>

Figure 5.9 Simulation results for medical images –MRI Brain 1, MRI - Brain MRI Abcess and MRI - Brain Cerebral using RT
Medical Image - MRI - Brain Cerebral

Input Image

Output Image - RT

<table>
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<th>Ridgelet</th>
</tr>
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<td>RMSE</td>
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Figure 5.9 (Continued)

5.5 CURVELET TRANSFORM

The Curvelet Transform was developed by Candès and Donoho (1999). This Transform is applicable for images with large number of curves. It is an advanced form of the Wavelet Transform and a multiscale Transform that allows an almost optimal sparse representation of the objects with edges. It has a very high degree of directional specificity. The Curvelet Transform has the directional parameters and the Curvelet pyramid contains high degree of anisotropic scaling principle it is slightly different from the process of isotropic scaling of Wavelets.

The curvelets are a non-adaptive technique for multi-scale object representation. Being an extension of the wavelet idea, they are becoming popular in image processing and scientific fields. Curvelets are an appropriate basis for representing images which are smooth apart from singularities along smooth curves, i.e. where objects in the image have a minimum length scale.
This property holds for cartoons, geometrical diagrams, and text. As one zooms such images, the edges appear increasingly straight. The curvelets take advantage of this property, by defining the higher resolution Curvelets to be skinnier the lower resolution curvelets. However, natural images photographs do not have this property they have the details at every scale. Therefore, for natural images, it is preferable to use some sort of directional wavelet transform whose wavelets have the same aspect ratio at every scale. The Curvelet transform has evolved as a tool for the representation of curved shapes in graphical applications. Then, it was extended to the fields of edge detection and other image applications.

**Characteristics:** The motivation for the using of the Curvelet transform is due to the following characteristics that are very specific to the Curvelet Transform.

1. Optimally sparse representation of objects

The Curvelets provide a kind of the sparse representation of the objects that tend to form a greater amount of the smoothness in the images. This phenomenon would greatly impart to the image compression greatly. The successful application of this statistics is that the process of the image compression could be done even from a noisy image and finally, the parameter Mean Square Error (MSE) could be obtained. The sparse representation of objects is shown in the Figure 5.10

![Figure 5.10 Sparse representation of object](image)
2. Optimally sparse representation of Wave Propagators

As the Curvelet is an advanced form of the wavelet transform, they could be applied for the geometry of the wave propagation. This Curvelet Transform could be well applied for the images and they could be approximated by simple translation of the images using the Hamiltonian flows.

The non directional Curvelet transform is shown in the Figure 5.11 given below.

![Figure 5.11 Non directional Curvelet Transform](image)

3. Optimal image reconstruction in severely ill-posed problem

Curvelets also have special micro local features which make them especially adapted to certain reconstruction problems with missing data. For example, in many important medical applications, one wishes to reconstruct an object $f(x_1, x_2)$ from noisy and incomplete tomographic data (Candes et al 2004), i.e., a subset of line integrals of $f$ corrupted by additive noise modelling uncertainty in the measurements.
Because of its relevance in biomedical imaging, this problem has been extensively studied. So far, Curvelets offer surprisingly new quantitative insights.

For example, a beautiful application of the phase-space localization of the Curvelet transform allows a very precise description of those features of the object of $f$ which can be reconstructed accurately from such data and of those features which cannot be recovered. The data acquisition geometry separates the Curvelet expansion of the object into two pieces.

The first part of the expansion can be recovered accurately while the second part cannot. The interesting thing here is that one can probably reconstruct the recoverable part with an accuracy similar to that one would achieve even if one had complete data. There is indeed a quantitative theory showing that for some statistical models which allow for discontinuities in the object to be recovered, there are simple algorithms based on the shrinkage of Curvelet biorthogonal decompositions, which attain optimal statistical rates of convergence, that is, such that there are no other estimating procedure which, in an asymptotic sense, give fundamentally better MSE.

The pseudo polar tiling of the frequency plane with trapezoids is already well-established as a data-friendly alternative to the ideal polar tiling. The first construction is that of Curvelet and is based on a cascade of properly sheared directional filters. On the other hand, Curvelet packets are defined directly in the frequency plane via interpolation onto a pseudo polar grid aligned with the trapezoids. In a nutshell, the two implementations differ in the way Curvelets at a given scale and angle is translated with respect to each other.
**Simulation Results**: Figure 5.12 shows that Input Image, Denoised Image, Quantized Image, Thresholded Image and Compressed output Image Curvelet transform.

![Images of simulation results](image_url)

**Figure 5.12 Simulation results for medical image CT using CVT**
Figure 5.13  Simulation results for medical images –MRI Brain 1, MRI – Brain, MRI Abcess and MRI - Brain Cerebral using CVT
Medical Image - MRI - Brain Cerebral

Input Image  

Output Image-CVT

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<td>RMSE</td>
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**Figure 5.13 (Continued)**

### 5.6 CONTOURLET TRANSFORM

The contourlet transform can deal effectively with piecewise smooth images with smooth contours, was proposed by Minh N Do and Martin Vetterli. The resulting image expansion is a directional multiresolution analysis framework composed of contour segments, and named as contourlet. This will overcome the challenges of wavelet and curvelet transform. Contourlet transform is a double filter bank structure. It is implemented by the Pyramidal Directional Filter Bank (PDFB) which decomposes images into directional subbands at multiple scales.
Properties

i) Multiresolution- The representation should allow images to be successively approximated, from coarse to fine resolutions.

ii) Localization- The basis elements in the representation should be localized in both the spatial and the frequency domains.

iii) Critical sampling- For some applications (e.g., compression), the representation should form a basis, or a frame with small redundancy.

iv) Directionality- The representation should contain basis elements oriented at a variety of directions, much more than the few directions that are offered by separable wavelets.

v) Anisotropy- To capture smooth contours in images, the representation should contain basis elements using a variety of elongated shapes with different aspect ratio.

For typical images with smooth contours, expect a significant improvement of a curvelet like method over wavelets, which is comparable to the improvement of wavelets over the Fourier basis for one dimensional piecewise smooth signals.

Perhaps equally important, the curvelet construction demonstrates that it is possible to develop an optimal representation for images with smooth contours via fixed transform.

The figure shows the process of sub sampling in Figure 5.14.
Figure 5.14 Process of separating an image into subbands

In terms of structure the contourlet transform is a cascade of a Laplacian Pyramid and a directional filter bank. In essence, it first use a wavelet-like transform for edge detection, and then a local directional transform for contour segment detection. The contourlet transform provides a sparse representation for two dimensional piecewise smooth signals that resemble images.

Simulation Results: Figure 5.15 shows that Input Image, Denoised Image, Quantized Image, Thresholded Image and Compressed output Image Contourlet transform.
Simulation Results

a. Input Image

b. Decomposed Image

c. Quantized Image

d. Thresholded Image

e. Output Image

Figure 5.15 Simulation results for medical image CT using CNT
Medical Image - MRI - BRAIN 1

<table>
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Medical Image - MRI - Brain MRI Abscess

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Figure 5.16 Simulation results for medical images –MRI Brain 1, MRI - Brain MRI Abscess and MRI - Brain Cerebral using CNT
Medical Image - MRI - Brain Cerebral

![Input Image](image1)

![Output Image-CNT](image2)

<table>
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<tr>
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<th>Contourlet</th>
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<td>RMSE</td>
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**Figure 5.16 (Continued)**

**Quantitative Comparison:** Table 5.1 gives the comparison results for sample medical images CT, FLIR, RIBS and MRI using WT, CVT, CNT and RT with the parameters CR, PSNR and RMSE.

**Table 5.1 Comparison results for Medical Images**

<table>
<thead>
<tr>
<th>Input Image</th>
<th>Wavelet Transform</th>
<th>Curvelet Transform</th>
<th>Contourlet Transform</th>
<th>Ridgelet Transform</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>CR</td>
<td>PSNR (dB)</td>
<td>RMSE</td>
<td>CR</td>
</tr>
<tr>
<td>CT</td>
<td>0.14</td>
<td>16.95</td>
<td>3.77</td>
<td>0.04</td>
</tr>
<tr>
<td>FLIR</td>
<td>0.31</td>
<td>10.99</td>
<td>7.42</td>
<td>0.02</td>
</tr>
<tr>
<td>RIBS</td>
<td>0.32</td>
<td>2.42</td>
<td>19.64</td>
<td>0.01</td>
</tr>
<tr>
<td>MRI</td>
<td>0.35</td>
<td>10.44</td>
<td>7.91</td>
<td>0.02</td>
</tr>
</tbody>
</table>
Table 5.2 gives the comparison results for sample medical images Axial traumatic brain injury - MRI using WT, CVT, CNT and RT.

**Table 5.2 Comparison results Medical Image - Axial traumatic brain injury-MRI**

<table>
<thead>
<tr>
<th>Transforms</th>
<th>WT</th>
<th>Curvelet</th>
<th>Contourlt</th>
<th>Ridgelet</th>
</tr>
</thead>
<tbody>
<tr>
<td>Compression Ratio</td>
<td>0.3941</td>
<td>0.0320</td>
<td>0.1265</td>
<td>0.7259</td>
</tr>
<tr>
<td>PSNR (dB)</td>
<td>11.7960</td>
<td>28.0102</td>
<td>33.1087</td>
<td>57.8881</td>
</tr>
<tr>
<td>RMSE</td>
<td>68.1535</td>
<td>12.9615</td>
<td>5.5592</td>
<td>2.8398</td>
</tr>
</tbody>
</table>

Table 5.3 gives the comparison results for sample medical images brain1 image - using WT, CVT, CNT and RT.

**Table 5.3 Comparison results Medical Image - Brain1 Image**

<table>
<thead>
<tr>
<th>Transforms</th>
<th>WT</th>
<th>Curvelet</th>
<th>Contourlet</th>
<th>Ridgelet</th>
</tr>
</thead>
<tbody>
<tr>
<td>Compression Ratio</td>
<td>0.3593</td>
<td>0.0165</td>
<td>0.1023</td>
<td>0.7659</td>
</tr>
<tr>
<td>PSNR (dB)</td>
<td>8.2486</td>
<td>27.9994</td>
<td>33.1236</td>
<td>57.9409</td>
</tr>
<tr>
<td>RMSE</td>
<td>101.2961</td>
<td>14.1096</td>
<td>5.7579</td>
<td>3.5160</td>
</tr>
</tbody>
</table>

Figure 5.17 shows the comparison results of medical images CT using WT, CVT, CNT and RT with PSNR values.
Figure 5.17 PSNR Vs Transforms for Medical Image 1 CT

**Results and Discussion:** From the tables and graphs given above, The Compression Ratio (CR) and the Peak Signal to Noise Ratio (PSNR) is very less in Wavelet transform and it increases along Curvelet and Contourlet transforms and better Compression Ratio and Peak Signal to Noise Ratio are obtained in Ridgelet transform. Hence, the image is compressed to a greater extent and noise is greatly reduced in Ridgelet transform. The Mean Square Error (MSE) is also less in Ridgelet transform. Therefore, it will conclude that the Ridgelet Transform is the suitable transform as compared with the other transforms which gives better image quality and reconstruction.

### 5.7 IMAGE COMPRESSION USING WAVELET BASED TRANSFORM

The wavelet transform is proved powerful in many signal and image processing applications such as compression, noise removal, and feature extraction, wavelets are not optimal in capturing the two dimensional singularities found in images. In particular, natural images consist of edges
that are smooth curves and which cannot be captured efficiently by the wavelet transform. Therefore, several new transforms have been proposed for image signals. The curvelet,contourlet and ridgelet transforms are some of the new geometrical image transforms, which can efficiently represent images containing curves, contours, twists, turns and textures.

5.7.1 Wavelet Based Ridgelet Transform

To improve the performance of the encoder, the non-redundant Wavelet Based Transform (WBT) in conjunction with a fast algorithm can be used to construct an embedded image coder. Due to differences in parent child relationships between the WBT coefficients and wavelet coefficients, an elaborated repositioning algorithm developed for the WBT coefficients in such a way that it could have similar spatial orientation trees as the ones used for scanning the wavelet coefficients.

The proposed Wavelet based linking transforms achieves both radial and angular decomposition to an arbitrary extent and obeys the anisotropy scaling law. Compared to the mentioned DFB based non redundant transforms, WBT can easily be realized by applying DFB on the wavelet coefficients of an image.

The wavelet based transform is mainly used for getting better values of compression and image quality. It gains much PSNR values. The noise in the compressed image is greatly reduced and therefore the resultant image can be acquired with good image quality.

Simulation Results: Figure 5.18 shows that input image, RT image and WBRT image
Figure 5.18 Simulation result for Medical image 1 CT using WBRT
Medical Image - MRI - BRAIN 1

![Input Image](image1) ![Output Image – WBRT](image2)

<table>
<thead>
<tr>
<th>Parameters / Transform</th>
<th>WBRT</th>
</tr>
</thead>
<tbody>
<tr>
<td>CR</td>
<td>0.6240</td>
</tr>
<tr>
<td>PSNR (dB)</td>
<td>58.8212</td>
</tr>
<tr>
<td>RMSE</td>
<td>1.9124</td>
</tr>
</tbody>
</table>

Medical Image - MRI - BRAIN MRI ABCESS

![Input Image](image3) ![Output Image - WBRT](image4)

<table>
<thead>
<tr>
<th>Parameters / Transform</th>
<th>WBRT</th>
</tr>
</thead>
<tbody>
<tr>
<td>CR</td>
<td>0.7213</td>
</tr>
<tr>
<td>PSNR (dB)</td>
<td>58.7652</td>
</tr>
<tr>
<td>RMSE</td>
<td>2.0214</td>
</tr>
</tbody>
</table>

Figure 5.19  Simulation results for medical images –MRI Brain 1, MRI - Brain MRI Abcess and MRI - Brain Cerebral using WBRT
Medical Image - MRI - Brain Cerebral

Input Image  Output Image - WBRT

<table>
<thead>
<tr>
<th>Parameters / Transform</th>
<th>WBRT</th>
</tr>
</thead>
<tbody>
<tr>
<td>CR</td>
<td>0.7419</td>
</tr>
<tr>
<td>PSNR (dB)</td>
<td>59.1544</td>
</tr>
<tr>
<td>RMSE</td>
<td>2.2154</td>
</tr>
</tbody>
</table>

Figure 5.19 (Continued)

5.7.2 Wavelet Based Curvelet Transform

In this, Wavelet based curvelet transform and the coefficients are taken from the wavelet transform and they are linked with the curve transform. In the curvelet transform, the image is directly decomposed and then the image is compressed. In the contourlet transform, a Laplacian Pyramid is employed for the first stage, while Directional Filter Banks (DFB) is used in the angular decomposition stage. Due to the redundancy of the Laplacian pyramid, the contourlet transform has a redundancy factor of 4/3 and hence, it may not be the optimum choice for image coding applications.

The proposed Wavelet based linking transforms achieves both radial and angular decomposition to an arbitrary extent and obeys the anisotropy scaling law. Compared to the mentioned DFB based non redundant transforms, the Wavelet Based Transform (WBT) can easily be realized by applying DFB on the wavelet coefficients of an image.
Simulation Results: Figure 5.20 shows the input image, CVT image, and WBCVT.

Figure 5.20 Simulation result for Medical image 1CT using WBCVT
Medical Image - MRI - BRAIN 1

Input Image                  Output Image-WBCVT

<table>
<thead>
<tr>
<th>Parameters / Transform</th>
<th>WBCVT</th>
</tr>
</thead>
<tbody>
<tr>
<td>CR</td>
<td>0.6351</td>
</tr>
<tr>
<td>PSNR (dB)</td>
<td>29.0221</td>
</tr>
<tr>
<td>RMSE</td>
<td>14.0635</td>
</tr>
</tbody>
</table>

Medical Image - MRI - Brain MRI Abcess

Input Image                  Output Image - WBCVT

<table>
<thead>
<tr>
<th>Parameters / Transform</th>
<th>WBCVT</th>
</tr>
</thead>
<tbody>
<tr>
<td>CR</td>
<td>0.5163</td>
</tr>
<tr>
<td>PSNR (dB)</td>
<td>28.2154</td>
</tr>
<tr>
<td>RMSE</td>
<td>13.9637</td>
</tr>
</tbody>
</table>

Figure 5.21  Simulation results for medical images - MRI Brain 1, MRI - Brain MRI Abcess and MRI - Brain Cerebral using WBCVT
Medical Image - MRI - Brain Cerebral

![Input Image](image1) ![Output Image - WBCVT](image2)

<table>
<thead>
<tr>
<th>Parameters / Transform</th>
<th>WBCVT</th>
</tr>
</thead>
<tbody>
<tr>
<td>CR</td>
<td>0.5235</td>
</tr>
<tr>
<td>PSNR (dB)</td>
<td>28.7876</td>
</tr>
<tr>
<td>RMSE</td>
<td>13.6521</td>
</tr>
</tbody>
</table>

**Figure 5.21 (Continued)**

### 5.7.3 Wavelet Based Contourlet Transform

This transforms uses a structure, which is a stage of subband decomposition followed by a directional transform. In the curvelet transform, the image is directly decomposed and then the image is compressed. In the contourlet transform, a Laplacian Pyramid is employed for the first stage, while Directional Filter Banks (DFB) is used in the angular decomposition stage. Due to the redundancy of the Laplacian pyramid, the contourlet transform has a redundancy factor of 4/3 and hence, it may not be the optimum choice for image coding applications.

The proposed Wavelet based linking transforms achieves both radial and angular decomposition to an arbitrary extent and obeys the anisotropy scaling law. Compared to the mentioned DFB based non redundant
transforms, the Wavelet Based Transform (WBT) can easily be realized by applying DFB on the wavelet coefficients of an image.

**Simulation Results:** Figure 5.24 shows that input image, CNT image and WBCNT.

![Input Image](image1)

![Contourlet Image](image2)

![Wavelet Based Contourlet Image](image3)

Figure 5.22 Simulation result for Medical image 1 CT using WBCNT
Medical Image - MRI - BRAIN 1

Input Image  
Output Image - WBCNT

<table>
<thead>
<tr>
<th>Parameters / Transform</th>
<th>WBCNT</th>
</tr>
</thead>
<tbody>
<tr>
<td>CR</td>
<td>0.3226</td>
</tr>
<tr>
<td>PSNR (dB)</td>
<td>34.2928</td>
</tr>
<tr>
<td>RMSE</td>
<td>5.9058</td>
</tr>
</tbody>
</table>

Medical Image - MRI - Brain MRI Abcess

Input Image  
Output Image - WBCNT

<table>
<thead>
<tr>
<th>Parameters / Transform</th>
<th>WBCNT</th>
</tr>
</thead>
<tbody>
<tr>
<td>CR</td>
<td>1.2148</td>
</tr>
<tr>
<td>PSNR (dB)</td>
<td>33.9694</td>
</tr>
<tr>
<td>RMSE</td>
<td>5.9854</td>
</tr>
</tbody>
</table>

Figure 5.23 Simulation results for medical images –MRI Brain 1, MRI - Brain MRI Abcess and MRI - Brain Cerebral using WBCNT
Medical Image - MRI - Brain Cerebral

Input Image  

Output Image-WBCNT

<table>
<thead>
<tr>
<th>Parameters / Transform</th>
<th>WBCNT</th>
</tr>
</thead>
<tbody>
<tr>
<td>CR</td>
<td>1.0212</td>
</tr>
<tr>
<td>PSNR (dB)</td>
<td>34.0142</td>
</tr>
<tr>
<td>RMSE</td>
<td>5.3124</td>
</tr>
</tbody>
</table>

Figure 5.23 (Continued)

Quantitative Comparison: Table 5.4 gives the comparison results for sample medical images CT, RIBS, MRI and FLIR using WBCVT, WCNT, and WBRT with the parameters CR, PSNR and RMSE.

Table 5.4 Comparison Results for Medical Images

<table>
<thead>
<tr>
<th>Input image</th>
<th>Wavelet Based Curvelet Transform</th>
<th>Wavelet Based Contourlet Transform</th>
<th>Wavelet Based Ridgelet Transform</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>CR</td>
<td>PSNR (dB)</td>
<td>MSE</td>
</tr>
<tr>
<td>CT</td>
<td>0.030</td>
<td>28.00</td>
<td>10.34</td>
</tr>
<tr>
<td>RIBS</td>
<td>0.032</td>
<td>28.01</td>
<td>14.62</td>
</tr>
<tr>
<td>MRI</td>
<td>0.033</td>
<td>28.00</td>
<td>11.53</td>
</tr>
<tr>
<td>FLIR</td>
<td>0.037</td>
<td>27.99</td>
<td>12.22</td>
</tr>
</tbody>
</table>
Figure 5.24 shows the comparison results of medical images CT using WCNT, CVT, WBCVT and WBRT with PSNR values.

![PSNR Graph](image)

**Figure 5.24 PSNR Vs Wavelet Based Transforms for Medical Image CT**

Figure 5.25 shows the comparison results of medical images CT using WCNT, WBCVT and WBRT with RMSE values.

![MSE Graph](image)

**Figure 5.25 MSE Vs Wavelet Based Transforms for Medical Image CT**
**Results and Discussion** From the tables and graphs given above, the following result may be concluded.

The Compression Ratio (CR) and the Peak Signal to Noise Ratio (PSNR) is less in Wavelet based Curvelet transform, and it increases in Wavelet based Contourlet transform and better Compression Ratio and Peak Signal to Noise Ratio are obtained in Wavelet based Ridgelet transform. Hence the image is compressed to a great extent and noise is greatly reduced in Wavelet based Ridgelet transform. The Mean Square Error (MSE) is also less in Wavelet based Ridgelet transform. Hence it may conclude that the Wavelet Based Ridgelet Transform is the suitable transform as compared with the other transforms which gives better image quality and reconstruction.

**5.8 SUMMARY**

This is a world of images. There is hardly to find a world without the presence of images. And as a result of this Image compression the uploading and the downloading of images could be performed at blasting speeds. Thus as a whole compression have been done in various technical aspects as performing compression using three different types of transforms as the Wavelet, Curvelet, Contourlet and the Ridgelet Transforms. In addition to this the compression is also done by the linking process as the Wavelet Based Transform. The final comparison result can conclude to the fact that the Ridgelet Transform forms the good compression. Better Compression Ratio and Peak Signal to Noise Ratio are obtained in Ridgelet Transform. The image is compressed to a great extent and noise is greatly reduced in Wavelet based Ridgelet transform. The Root Mean Square Error (RMSE) is also less in Wavelet based Ridgelet transform. Hence it may conclude that the Wavelet Based Ridgelet Transform is the suitable transform as compared with the other transforms which gives better image quality and reconstruction. Since the need for the compression of the images are an integral part the
forthcoming generation of the faster download speed of the images this compression would certainly lead to the fastest world of the images and the videos for the communication to take place.