CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION

The explosive growth of multimedia applications generates huge volume of data that has to be stored and transmitted. Hence, data compression has become a necessity to reduce the storage space and transmission time. Image compression is an important research area due to inherent size of the image and the increasing number of applications that transmit images, especially mobile, satellite communications and telemedicine. Images contain redundancy due to the correlation between adjacent pixels and this can be exploited for compression. Compression can be lossless or lossy, and generally images are compressed using lossy techniques, utilizing the limitations of the human visual system. Progressive compression is suitable for transmitted images since reconstruction is possible with any number of bits received. The fidelity of the reconstruction improves as more bits are received and decoded. During transmission, noise in the channel and fading effects introduce errors in the bit stream. To combat this, effective error protection is required. Therefore, image transmission requires source coding for compression and channel coding for error protection.

1.2 NEED FOR PROGRESSIVE COMPRESSION

Compression could be sequential or progressive. In sequential compression, the entire image is coded in one pass and all the bits are required for reconstruction. The image is reconstructed from top to bottom.
after receiving and decoding all the transmitted bits. In progressive compression, the entire image is coded in multiple passes, generating an embedded (layered) bit stream. The reconstruction can be done with any number of passes (or bits). The image is reconstructed as a coarse approximation with the base layer and the subsequent enhancement layers add details to improve the quality.

The modern image processing systems generate large amount of data that is stored, processed or transmitted. The growth of mobile communications, internet and other wireless networks have led to the transmission of images over bandlimited channels and the cost incurred is directly related to the transmission time. The browsing and downloading of images stored in remote databases is one of the common applications that require image transmission. When the image is encoded in a layered manner, it is scalable with respect to quality. The image reconstructed with the first few bits received can be used to decide whether the rest of the data is required or not, thus eliminating wastage of resources. Thus, the progressive coding scheme is attractive for real-time applications such as remote browsing and retrieval of images through wireless networks.

When the image is encoded in a layered manner, the most important information is in the base layer that reproduces a coarse approximation of the image. The subsequent enhancement layers incrementally improve the image quality when decoded in the order of their importance. When channel coding is applied, it introduces redundancy into the bit stream. This redundancy is constant for the entire bit stream in the case of an equal error protection (EEP) scheme, whereas it can be reduced progressively in the unequal error protection (UEP) scheme. This UEP scheme is apt for image transmission, where the base layer is given heavy
protection and it is reduced for the other layers based on their importance. This is one of the important advantages of the progressive coding technique.

1.3 MOTIVATION FOR THE RESEARCH

Image compression has emerged as a major research area due to the phenomenal growth of applications that generate, process, store and transmit images. Some of the applications of image processing are medical diagnostics, weather forecasting, remote sensing, digital photography, wireless / mobile communications, internet, etc. The large memory required for storing an image and the constrained bandwidth of the communication channels necessitates compression. The channel conditions create random errors in the transmitted bit streams due to AWGN as well as fading. This creates the need for error resilient coding to protect the transmitted data and efficient methods that are adaptive to the channel conditions are a subject of research.

Progressive coding techniques generate an embedded bit stream and the fidelity of the reconstruction depends on the number of bits received. The compressed bit streams are organized in layers, that is scalable in quality or resolution and other features like region-of-interest coding, error resilience, security, etc. can be incorporated. Progressive compression is the natural choice for image transmission since the transmission can be terminated at any time if the reconstruction is found to be unsuitable. This technique is very effective for reducing the wastage of resources in terms of time and cost. Many techniques are available for image compression of which the transform-based techniques are efficient and popular. The transformation of the image generates a sparse representation that is encoded and transmitted. The efficiency of the transform depends on the energy compaction (that is, number of zero coefficients) and time complexity. The compression achieved depends on the type of transform and encoding method.
The discrete cosine transform (DCT) achieves good energy compaction, generates real coefficients and is part of the Joint Photographic Experts Group (JPEG) standard. But the DCT does not have multi-resolution capability and this drawback is overcome in the discrete wavelet transform (DWT). The DWT is part of the JPEG2000 standard due to its several advantages. The DWT is naturally applicable for progressive compression of images because of its multi-resolution property. It achieves excellent energy compaction and generates an embedded bit stream. The conventional DWT is a separable transform where the two-dimensional (2D) transform is computed using two one-dimensional (1D) transforms. The DWT can also be implemented using a non-separable 2D lattice with lifting that is better for images with high correlation in all directions.

Natural images contain edges, geometry, texture and other discontinuities / details that are oriented in various directions. Wavelets are not efficient in capturing discontinuities along directions other than horizontal, vertical and diagonal because their basis functions have a square support. This disadvantage is overcome with the non-linear wavelets. The non-linear wavelet transforms are 2D transforms that are not separable like the conventional wavelets. They have elongated basis functions that can be oriented in various directions depending on the information content in the image. Several non-linear wavelets have been proposed in the literature each with their own capability in capturing information in images. In this work, three non-linear wavelets have been applied in progressive compression of images – contourlets, bandelets and ridgelets. Contourlets are suitable for images with curved lines or contours, bandelets are effective in capturing texture information and ridgelets are efficient for images with straight edges.

Existing algorithms have been modified to compress the non-linear transformation coefficients with data structures similar to existing DWT.
1.4 **OBJECTIVE OF THE THESIS**

The objective of the thesis is to investigate:

- Progressive compression algorithms that facilitate quality scalable reconstructions.
- Efficient compression algorithms suitable for different transforms.

1.5 **FOCUS OF RESEARCH WORK**

The research work investigates progressive coding of images for wireless transmission with certain algorithms based on DCT, DWT and non-linear wavelet transforms. The sequential and progressive modes of JPEG based on DCT have been modified, and their performance in wireless channels has been investigated. The lifting implementation of DWT has been applied for image compression and the separable DWT has been compared with the 2D non-separable implementation. The non-linear wavelets have been applied in conjunction with the conventional DWT and the compression algorithms modified accordingly to be used with the non-linear transforms. The non-linear wavelet transforms that have been investigated in this work are contourlets, bandelets and ridgelets.

The parameters used for the evaluation of the various algorithms are compression ratio (CR), bits per pixel (bpp), mean squared error (MSE), peak signal-to-noise ratio (PSNR) and bit error rate (BER). CR is the parameter that is used as a measure of compression. It is defined as the ratio of the number of bits representing the image before compression to the number of bits after compression, expressed as a percentage. The compression is also indicated by the parameter ‘bits per pixel’. ‘bpp’ is defined as the ratio of the total number of bits representing the image after compression to the
size of the original image. The distortion in the reconstructed image depends on the compression. Higher the compression, more information is discarded, increasing the distortion and vice versa. Distortion is measured by MSE defined as,

\[
MSE = \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} (x(i,j) - \hat{x}(i,j))^2
\]  

(1.1)

where M x N is the size of the image, \(x(i,j)\) is the original pixel value at coordinates \((i,j)\) and \(\hat{x}(i,j)\) is the reconstructed pixel value. PSNR is defined as the ratio of the square of the peak value of the image to the MSE, expressed in decibels (dB). Bit error rate (BER) is defined as the ratio of the number of bits in error to the total number of bits transmitted.

1.5.1 Discrete Cosine Transform

JPEG was established in 1992 as the first International standard for still image compression. It is based on the DCT and is suitable for continuous-tone images with wide range of applications. JPEG has one lossless mode based on predictive coding and three lossy modes – baseline sequential, progressive, and hierarchical. The baseline sequential mode divides the input image into blocks of size 8 x 8, transforms the blocks using DCT, quantizes the coefficients and encodes them with a combination of run length and Huffman coding. There are two progressive modes in JPEG – spectral selection and successive approximation - both are multiple pass algorithms. In each pass of the spectral selection algorithm, the coefficients of different spectral bands are encoded. The spectral bands are formed by scanning the coefficients of a block in zigzag order, and grouping 'p' number of coefficients together. DC coefficients are encoded in the first pass (base layer) using the differential mode. AC coefficients are grouped and encoded in subsequent enhancement layers. The number of layers or passes is fixed by the application. In successive approximation, the coefficients are reduced in
precision by a point transform. The coefficients with reduced precision are encoded and transmitted in the first pass (starting from the most significant bit). In successive passes, one additional bit of every coefficient is transmitted, increasing the precision at the receiver with every pass. This is continued till the least significant bit is reached. Successive approximation is computationally more complex than spectral selection, with improvement in performance.

One of the most important drawbacks in JPEG is the annoying blocking artifacts in the reconstructed image when the bit-rate is reduced. This degradation in the low bit-rate quality limits the compression that can be achieved. In this work, an averaging and filtering (Wiener / Median) approach has been proposed to improve the PSNR at low bit-rates and hence the visual quality of the reconstructed image is enhanced. This filtering operation reduces the sharpness in the image and it has been improved by contrast stretching. The proposed approach can be applied for both sequential and progressive modes. Moreover, it is proposed to replace the Huffman coding stage in JPEG, both sequential and progressive, with vector quantization (VQ). VQ is a lossy compression technique that encodes sequence of symbols. In image compression with VQ, the source vectors are obtained by parsing the image into rectangular blocks of size ‘\( k = m \times n \)’. A codebook stores the code vectors that are the approximations to the original samples. The source vector is compared with each and every entry of the codebook to find the closest match that best approximates the input vector. The matching code vector with the smallest distortion is the best approximation and its address in binary form is transmitted to the receiver. The receiver also has to store a similar codebook and decoding is a simple table lookup operation. The codebook is designed based on the Linde-Buzo-Gray (LBG) algorithm.
This proposed modification of applying VQ increases the compression, improves the low bit-rate quality and makes the image resilient to errors during transmission. The proposed approach also gives an improvement in PSNR over the conventional JPEG. When the variable-length Huffman code is replaced with fixed-length VQ, the image becomes resilient to errors. The errors in VQ encoded images corrupt only certain portions of the image and this does not lead to error propagation as in Huffman coding. When progressive compression is used, UEP can be employed for the different layers in the embedded bit stream. The rate of the channel code can be varied according to the importance of the layer, thus reducing the redundancy. The performance of the baseline sequential and spectral selection modes has been evaluated with punctured convolutional codes (PCC) in Additive White Gaussian Noise (AWGN) and Rayleigh fading channels.

The binary convolutional codes (CC) are optimal because they have the largest possible free distance for a given constraint length. The rate 1/2, constraint length 7 convolutional code with Viterbi decoding has been applied here for image coding, since it is widely used in many communication applications. The hardware is readily available and high rate codes are obtained from this basic code by puncturing. The puncturing pattern determines the rate of the code. The puncturing patterns used here are:

- Rate 6/11 [1 1 1 1 1 1 1 1 1 0]
- Rate 4/7 [1 1 1 1 1 1 0]
- Rate 5/8 [1 1 1 0 1 1 1 0]

The performance depends on the convolutional encoder design as well as the puncturing pattern. The received images have been evaluated based on the quality for different signal-to-noise ratios ($E_b/N_0$) on the channel. An UEP
scheme using punctured convolutional codes has been applied on the compressed images and their performance compared with EEP schemes.

1.5.2 Discrete Wavelet Transform

The DWT has excellent energy compaction and the reconstruction is superior to other transforms. Most important, the DWT eliminates blocking artifacts at low bit-rates that occurs in DCT-based JPEG. DWT can be computed with fast algorithms using either filtering or lifting methods. In the filtering method, the input image is convolved with the basis matrix and the output is the wavelet coefficients at different scales. In the lifting method, the spatial domain pixel values are used in computing the transform and the resulting coefficients are stored in-place. This makes the lifting technique more memory efficient compared to the filtering method. The JPEG2000 standard for image compression is based on the DWT and two wavelets from the Daubechies family are specified in the standard – db9/7 and db5/3. Db9/7 is for lossy compression since it uses floating point representation and db5/3 is for lossless compression since it is integer-to-integer representation (with lifting) and leads to perfect reconstruction.

In this work, it is proposed to use three wavelets for progressive image compression – db9/7, db5/3 and Haar. The Haar wavelet has been chosen for comparison because it is computationally simple and does not have boundary value problems. The performance of db9/7 and db5/3 wavelets with bit plane coding (BPC), based on filtering and lifting have been compared. The db9/7 wavelet performs better than the db5/3 wavelet (lossy compression) in terms of PSNR for most of the test images except for images with more details. The performance of the existing Haar wavelet and its modifications have been analyzed with lifting and BPC. The lifting steps of the first order Haar wavelet has been reversed, with update followed by predict steps. This modified Haar wavelet gives higher PSNR than the
conventional order of predict followed by update. The first order Haar predictor has been extended to the third order and it is found that the extended Haar wavelet gives superior results compared to the other three wavelets, especially at low bit-rates. The non-separable 2D lifting wavelet transform based on the quincunx lattice has been applied for image compression and compared with its equivalent separable db5/3 wavelet. It is found that for images with features that are oriented in all directions, the 2D transform is superior to the separable transform. The resulting coefficients are stored in-place and the coefficients have been reordered to obtain a data structure similar to the Mallat decomposition. At each level of decomposition, the coefficients are separated into two bands – approximations and detail. In the conventional wavelet transform, there are four subbands for one level – one approximation and three detail subbands, one for each of the horizontal, vertical and diagonal details. A progressive compression algorithm with VQ for the 2D structure of quincunx lifting has been applied.

The BPC algorithm has been applied in this work to progressively encode the input image, generating an embedded bit stream that can be truncated at any bit-rate. The input image is decomposed into subbands at various levels with DWT. The highest level (approximation) coefficients are quantized with the smallest step size and it is made coarser for the lower levels (details). The quantization step size for each subband ‘b’ is computed as shown below:

\[
q(i,j) = \text{sign}(p(i,j)) \left\lfloor \frac{|p(i,j)|}{\Delta_{b'}} + e \right\rfloor
\]

(1.2)

where \(\Delta_{b'} = \text{bss}. \frac{1}{\sqrt{G_{b'}}}\), \(G_{b'} = 2^{2^{level}}\), \(p(i,j)\) is the actual value of the coefficient, \(q(i,j)\) is the quantized coefficient, \('e'\) is a parameter that takes on values between 0 and 1, \(\Delta_{b'}\) is the step size for the subband 'b', 'bss' is the base step size, 'level' is the decomposition level for the subband 'b'. The
quantized coefficients in every subband are split into code blocks. Each code block can be coded independently producing a separate bit stream.

The coefficients within a code block are scanned in a pre-determined order and encoded. The algorithm uses context adaptive coding to efficiently represent the quantized transform coefficients. Context coding takes into account the surrounding bit patterns, and significant bit values in the neighborhood of the value under consideration. They are optimized for the target bit-rate. The standard supports fractional BPC with Lagrangian optimization. The decoder applies the inverse operations of the encoder to reproduce the input image. A key advantage of scalable compression is that the target bit-rate or reconstruction resolution need not be known at the time of compression. Since the algorithm deals with independent code blocks, these can be processed simultaneously thereby reducing the implementation time. Block processing enables usage of smaller memory as opposed to large amount of memory required by other algorithms which process the image as a whole. It has modest complexity and is resilient to errors.

1.5.3 Contourlets

Contourlets effectively capture smooth contours in the image using a rich set of basis functions. Contourlets have elongated support at various scales, directions and aspect ratios. It provides a sparse representation for images containing discontinuities across smooth curves. The contourlet transform (CT) is a multi-directional, multi-scale transform that is constructed by combining the Laplacian pyramid (LP) with the directional filter bank (DFB). It allows for different and flexible number of directions at each scale and uses iterated filter banks that makes it computationally efficient. The efficiency of the transform lies in its ability to capture the essential features of the image with few coefficients. This compact representation is useful for compression and image retrieval from data bases. The need for evolving a
better coding technique by combining the simplicity of the wavelet transform and efficient coding of geometrical surfaces by the contourlets leads to the wavelet-based contourlet transform (WBCT). As directional filter banks are not suitable to handle the low frequency content, the DFB is combined with a multi-scale decomposition (Mallat decomposition), where the low frequencies of the image are removed before applying the DFB. This is the principle of the new WBCT, which is a non-redundant transform.

The proposed method is to apply the DWT followed by contourlet transform on the input image; the number of decomposition levels will be decided by the size of the image and the application. The contourlet transform is applied on the lower level subbands of the wavelet decomposition. The WBCT output has been compressed with three progressive coding algorithms – Set Partitioning in Hierarchical Trees (SPIHT), Tag Setting in Hierarchical Trees (TSIHT) and BPC. The coefficients obtained from the WBCT are in different directional subbands. They have been repositioned to obtain the same spatial relationship among coefficients as in the wavelet decomposition tree. This spatial orientation tree structure has been utilized in SPIHT and TSIHT.

SPIHT is a progressive image compression technique that reproduces high quality images at low bit-rates. It is based on the spatial orientation tree structure of DWT. The essence of SPIHT algorithm is to identify which coefficients are significant, sort selected coefficients in each sorting pass, and transmit the ordered refinement bits. Three lists – List of Insignificant Sets (LIS), List of Insignificant Pixels (LIP) and List of Significant Pixels (LSP) – are maintained both at the transmitter and the receiver. In any pass, a coefficient is significant if it is greater than the threshold; otherwise it is insignificant. The initial value of the threshold is determined by the largest magnitude of all the coefficients. The wavelet
coefficients are partitioned into different subsets and the significance information of the subset of coefficients is conveyed during the *sorting pass*. The binary representation of the significant coefficients are transmitted, one bit in each *refinement pass*. The threshold value is reduced with every pass, till it reaches one.

During the *sorting pass*, if a coefficient is *significant*, its reconstruction value is $\pm 1.5 \times 2^n$, depending on the sign bit. During the *refinement pass*, depending on the sign of the received bit, the decoder adds $\pm 2^{n-1}$ to the reconstruction value of the *significant* coefficient. SPIHT is optimized for progressive coding. It is efficient and produces excellent results in terms of bpp and PSNR for transmitted images with suitable channel coding for error protection. The SPIHT algorithm has been applied here on the spatial orientation tree produced by the WBCT. The coefficients have been repositioned to produce the same data structure as the DWT and then it is compressed efficiently with SPIHT.

TSIHT is a new algorithm for progressive image coding which is an improved version of the SPIHT. TSIHT coding is the same as SPIHT but uses different data structures. TSIHT uses three tag flags - TSP (*Tag of Significant Pixels*), TIP (*Tag of Insignificant Pixels*) and TST (*Tag of Significant Trees*) to distinct different entries in LSP, LIP and LIS respectively. TSIHT coding keeps low bit-rate quality as SPIHT and has three improved features: lesser memory requirement, improved refinement pass and efficient depth-first-search. The advantages of TSIHT over SPIHT make it more favorable for hardware implementation and also in efficiency of coding and compressing an image.

The original algorithm in JPEG2000 standard has been modified here by replacing the DWT with WBCT. The coefficients of WBCT have
been scalar quantized and compressed using BPC. The scalar quantization step size has been modified to suit the contourlet coefficients that are present in the lowest two levels of the wavelet decomposition. The quantization step size is not increased for levels below three; the same step size is maintained. This is done because the contourlet transform is applied on the subbands of the last two levels and a larger step size causes loss of information carried by the contourlet coefficients.

The results have been compared for the three algorithms for six test images with three wavelets from different wavelet families. For every compression algorithm, the WBCT gives the best reconstruction if the image contains contours. The BPC algorithm is found to give better image quality than SPIHT and TSIHT for the same bit-rate. TSIHT and SPIHT are comparable in performance in terms of PSNR and fidelity of reconstruction, especially at low bit-rates. The visual quality of the reproduction is enhanced for images with contours and textures with WBCT than the DWT, even though the PSNR may be lower for some images.

1.5.4 Bandelets

The wavelet transform captures point singularities, but not along surfaces with geometric regularity. Bandelet transform is an orthogonal, multi-scale transform that captures the geometry in images. For natural images with smooth blurring and turbulent textures, the local description of geometric regularity does not lead to robust and efficient compression algorithms. Hence, any image representation technique should take advantage of the continuity of edges so that fewer coefficients are necessary for encoding. Bandelet bases are elongated in the direction of geometric flow. The discrete bandelet transform (DBT) applied directly on the image at a fixed scale is the mono-resolution bandelet transform. The drawback of the mono-resolution bandelet transform is that it is applied on blocks of the image
and therefore produces blocking artifacts at low bit-rates. Thus, the second
generation discrete wavelet-bandelet transform (DWBT) is proposed to
overcome this. The DWT is applied on the image and the quadtree computed
for every scale and orientation. The best geometry or direction is selected in
each square. The bandelet transform is applied on each leaf of the quadtree in
the best direction specified to produce the bandelet coefficients. The
redundancy in the wavelet transform is removed by bandeletization. The
wavelet coefficients that have large values near singularities are transformed
to very small values by the bandelet transform. Wavelets introduce visible
ringing effects whereas they are concealed in bandelets. Bandelets have
superior visual quality in the reconstructed image than the wavelets.

The results of applying DBT, DWT and DWBT on six test images
have been compared. The mono-resolution bandelet transform is applied
directly on blocks of the image and this leads to blocking artifacts in the
reconstructed image, as evident from the results. As the number of
coefficients used in the approximation is increased, the visual quality of the
image is enhanced and the blocking artifacts are less visible. When the
percentage of coefficients used in the reconstruction is greater than 50, the
bandelets are far superior to wavelets. The second generation DWBT acquires
the texture information in the image. The wavelet-bandelet coefficients are
quantized and encoded using modified BPC (MBPC) and the results have
been compared with SPIHT. The quadtree decomposition and the direction
information have to be encoded separately and transmitted along with the
coefficients. This incurs an additional overhead in bits that is not required
in wavelets. This is one of the disadvantages of the bandelet transform but it
is more than compensated by the superior visual quality of images with
textures.
1.5.5 Ridgelets

The ridgelet transform provides a sparse expansion for functions that have line singularities in 2D. It is based on the finite Radon transform (FRAT) that maps a line singularity into a point singularity. The DWT is applied on the Radon domain to capture the point singularity. The resulting finite ridgelet transform (FRIT) is orthonormal, non-redundant and invertible. The FRIT has been proposed to overcome the weakness of wavelets in higher dimensions. The FRAT gives projection sequences along different directions and the 1D DWT is applied on these projections, leading to ridgelet coefficients. The FRIT is suitable for images with straight edges but not optimal for images with curves. It can be implemented with fast algorithms. The orthonormal FRIT has been compared with the DWT and it has been found that the FRIT is superior to DWT for images with straight edge segments. The quality difference between ridgelet and wavelet reconstruction is visibly noticeable in all the test images chosen. The image quality is progressively enhanced as more coefficients are included in the reconstruction. It is evident from the displayed images that FRIT results in a better edge representation even with a considerably smaller number of significant coefficients.

In some FRAT projections, there may be strong periodic components that are better approximated by DCT than DWT. This has been proved for the six test images in the consistently higher PSNR obtained by switching between DWT and DCT. The border discontinuities of the image create large amplitude coefficients that can be eliminated by a symmetric periodic extension of the image. Applying the FRIT on such an image that has been symmetrically extended is called folded FRIT and takes care of the problem of large discontinuities. When the image is divided into blocks and the FRIT is applied on each block separately, edge segments are better
captured. The results of comparing the folded FRIT and the folded block FRIT demonstrate the superiority of the folded block FRIT over the folded FRIT.

The multilevel FRIT (MLFRIT) divides the input image into blocks and applies the orthonormal FRIT on each block to produce a coarse approximation and detail. This process can be iteratively done on the approximation to produce a subband decomposition similar to DWT. It has been shown by the resulting data structure that the MLFRIT is suitable for progressive compression of images. Based on MLFRIT and VQ, a novel progressive coding algorithm has been proposed for efficient image compression. In this method, the orthonormal MLFRIT is performed on the images and the resulting ridgelet coefficients are grouped appropriately and subjected to VQ. The proposed compression algorithm results have been presented extensively for a two level MLFRIT. This algorithm can be applied on images with larger size and higher levels of decomposition greater than two. Since ridgelet compression is inherently suitable for certain types of images / textures, especially for images with straight edges, it results in sparser image representation. Ridgelets take advantage of the image geometry, paving the path for better compression.

1.6 ORGANIZATION OF THESIS

The thesis contains totally five contributing chapters which investigate progressive compression of still images that makes it suitable for transmission through wireless channels.

Chapter 1 introduces the topic of research with the concept of source and channel coding for images, necessity for progressive compression, motivation and objective of the thesis and gives an overview of the research done in the field of progressive image compression.
Chapter 2 proposes modifications in the JPEG standard to overcome the blocking artifact problem at low bit-rates and also achieve higher compression. The DCT-based standard is used in almost all the practical applications for more than one decade since 1992. The performance of the modified algorithm with PCC has been evaluated for image transmission.

Chapter 3 uses the state-of-the-art wavelet-based techniques for compression and a performance analysis with the wavelets specified in the JPEG2000 standard. The lifting approach, which is suitable for real-time applications and hardware implementations due to its flexibility, simplicity and faster encoding / decoding has also been analyzed. The modifications to Haar wavelet and non-separable 2D quincunx lifting with VQ have been proposed for progressive coding.

Chapter 4 proposes the use of the contourlets to augment the performance of the wavelet-based techniques. The use of non-linear WBCT for compression of images with curved segments is investigated.

Chapter 5 proposes the use of second generation bandelets for progressive compression of images that is suitable for images with geometric patterns and textures.

Chapter 6 proposes the use of ridgelet transform and a progressive compression algorithm that is suitable for images with straight edge segments.

The conclusion and future extension of the proposed methods are given in Chapter 7. Finally, the references used in this research work and the papers published during the course of the research are listed.
1.7 CONCLUSION

In this thesis, progressive compression techniques for transmission of still images through fading, wireless channels have been investigated. The techniques used here are based on the DCT, DWT, and the non-linear contourlets, bandelets and ridgelets. The transformation coefficients have been compressed using modifications to the existing methods to adapt to the particular transform. The results of the above compression algorithms are extensively investigated.