CHAPTER I

INTRODUCTION
Introduction

The analysis of signals and phenomena at multiple scales of resolution has received a level of attention and interest in the past years. Fourier Transform (FT) is one of several mathematical tools that are useful in the signal analysis. This involves the decomposition of the signals in-terms of sinusoidal components. Fourier analysis is appropriate for periodic signals or for signals whose statistical characteristics do not change with time. Time-frequency analysis is very important in many signal-processing schemes, e.g. Transient signal analysis. Consequently, the Short Time Fourier Transform (STFT) was identified to be an adequate tool for time-frequency analysis. Dennis Gabor [1] gave an alternative to Fourier transforms and introduced STFT. The ideas in STFT is to window or time limit or localize the signal by using an appropriate window function and then evaluate the Fourier Transform locally, thus obtaining a representation as a function of both time and frequency. For good frequency resolution we have to use a wider window in the STFT, but this would lead to poor localization in time domain of the high frequency components. The converse is true for low frequency components when a narrow window for the STFT is used. The STFT is a linear time-frequency representation. The disadvantage of STFT is that once a window length is chosen, the resolution that is obtained in time and frequency domain remains fixed. There is no way of improving the frequency resolution towards the lower frequencies and the time resolution towards detecting high frequency transients. To overcome this problem in the mid 1980's a group of applied mathematicians began investigating in the use of a general class of functions, which had compact support in time and frequency domain. A cosine wave windowed by a "Gaussian" function is used. The
windowed cosine wave is compressed in time or expanded in time depending on whether one wants good time resolution or good frequency resolution. Since the localized window function has constant shape and also has a wave like appearance, it was referred to by Morlet [2] as constant wavelet. Later on the term constant was dropped and they were simply called as wavelets. Application of wavelet transform has almost come to be regarded as being synonymous with data compression. An important property of the wavelet basis is, it provides a Multiresolution analysis.

Fig. 1.1 a) Sine wave

The wavelet transform of a function $f(t)$ is defined as,

$$W_f(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} f(t) \psi \left( \frac{t-b}{a} \right) dt$$

........1.1
where, \( \psi (t) \) is the wavelet function chosen and the parameters \( 'a' \) and \( 'b' \) indicate the scale and time-shift respectively. Figures 1.1a & b show sinusoidal wave oscillating with equal amplitude over \( \infty \leq t \leq \infty \), having infinite energy and the wavelet having finite energy concentrated around a point respectively. It is known that wavelets have better energy concentration property than the Fourier transform, for signals with discontinuities. This is one of the main reasons that wavelet based compression methods usually out-perform Discrete Cosine Transforms (DCT)-based Joint Photographic Emission Group (JPEG), especially at low bit rate.

Table 1 shows the qualitative transition from simple text to full-motion video data and the disk space, transmission bandwidth, and transmission time needed to transmit such uncompressed data. This indicates the need for sufficient storage space, large transmission bandwidth, and long time for image, audio, and video data transmission.

<table>
<thead>
<tr>
<th>Multimedia Data</th>
<th>Size/Duration</th>
<th>Bits/Pixel (bpp) or Bits/Sample (bps)</th>
<th>Uncompressed Size</th>
<th>Transmission Bandwidth (b for bits)</th>
<th>Transmission Time (using a 28.8k Modem)</th>
</tr>
</thead>
<tbody>
<tr>
<td>A page of text</td>
<td>11&quot; x 8.5&quot;</td>
<td>Varying Resolution</td>
<td>4-8 KB</td>
<td>32-64 Kb/page</td>
<td>1.1-2.2 sec.</td>
</tr>
<tr>
<td>Telephone Quality speech</td>
<td>10 sec.</td>
<td>8 bps</td>
<td>80 KB</td>
<td>64 Kb/sec.</td>
<td>22.2 sec.</td>
</tr>
<tr>
<td>Gray scale Image</td>
<td>512 x 512</td>
<td>8 bpp</td>
<td>262 KB</td>
<td>2.1 Mb/image</td>
<td>1 min. 13 sec.</td>
</tr>
<tr>
<td>Color Image</td>
<td>512 x 512</td>
<td>24 bpp</td>
<td>786 KB</td>
<td>6.29 Mb/image</td>
<td>3 min. 39 sec.</td>
</tr>
<tr>
<td>Medical Image</td>
<td>2048x1680</td>
<td>12 bpp</td>
<td>5.16 MB</td>
<td>41.3 Mb/image</td>
<td>23 min. 54 sec.</td>
</tr>
<tr>
<td>SHD Image</td>
<td>2048x2048</td>
<td>24 bpp</td>
<td>12.58 MB</td>
<td>100 Mb/image</td>
<td>58 min. 15 sec.</td>
</tr>
<tr>
<td>Full-motion Video</td>
<td>640 x 480 (30 frames/sec), 1 minute</td>
<td>24 bpp</td>
<td>1.66 GB</td>
<td>221 Mb/sec.</td>
<td>5 days 8 hrs.</td>
</tr>
</tbody>
</table>
Wavelet transforms and their natural extension to wave packets are used to design efficient schemes for representing and compressing signals and images. This is an extremely active area of research and literature reveals the possibilities of several different lines of investigation. The Coifman and Wickerhauser [3] gives a summary of their wavelet packet method, as well as a technique using lapped window transforms, together with an algorithm that searches a dyadic tree for the best possible basis. DeVore, Jawerth and Lucier [4] formalize the image compression problem in a functional analysis setting. They analyze the errors produced by the quantization of the wavelet transform coefficients and explain how to match the error measure to Human Visual Sensitivity (HVS). The paper by Tewfik, et.al. [5] deals with the problem of adapting the choice of the wavelet itself in order to achieve the best scale limited approximation of a given signal. A significant aspect of this work is the choice of cost criteria that yield both good results and efficient algorithms. Exciting application areas of wavelet based signal processing is in seismic and geophysical signal processing. Applications of Denoising, compression and detection are all important especially with higher dimensional signals and images. Another application of wavelet based signal processing is Image processing in general and Biomedical signal and Image processing in particular.

Digitized images have replaced analog images as photographs or X-rays in many different fields. In their raw form, digital images require a tremendous memory capacity for storage and large amount of bandwidth for transmission. In the last two decades, many researchers are engaged in developing new techniques for image compression. A common characteristic of most of the images is that the
neighboring pixels are highly correlated and therefore contain highly redundant information. It is necessary to find an image representation in which the image pixels are decorrelated. Compression can be achieved by transforming the data, projecting it onto basis functions, applying a threshold and then encoding this transform [6]. Due to the nature of the image signal and human perception mechanism, the transform used must accept non-stationary and be well localized in both the space and frequency domains. Moreover it should exploit the psycho-visual as well as statistical redundancies in the image data to enable bit rate reduction. Although international standard for still image compression called JPEG [7] has been established by ISO and ECE, the performance of such coders generally degrades at low bit rates because of the underlying block based DCT scheme [8].

In DCT, the input image needs to be blocked and correlation across the block boundaries is not eliminated, resulting in noticeable and annoying blocking artifacts.

Wavelet transform solves this problem because there is no need to block the image. Wavelet based coding [9] provides substantial improvements in picture quality at higher compression ratios mainly due to the better energy computation property of wavelet transform. Wavelets are functions of limited duration and having average value of zero. These are generated from the single function by dilations and translations of

$$\psi_{a,b}(t) = |a|^{-1/2} \psi \left( \frac{t-b}{a} \right) \quad \text{(1.2)}$$

The definition of wavelets, as dilates of one function means that high frequency wavelets correspond to ‘a’< 1 or narrow width, while low frequency wavelets have
Daubechies [10,11] was first to discover that the discrete time filters or Quadrature Mirror Filters (QMF) can be iterated and under certain regularity conditions, will lead to continuous time wavelets. Since digital image is a discrete signal, so wavelet based image decomposition can be implemented using Finite Impulse Response (FIR) discrete time filters. Wavelet transform may be used to decompose a signal into various sub-bands such as uniform decomposition, octave band decomposition, adaptive or wavelet packet decomposition [9] etc.

In the octave band decomposition, we first pass each row of image through analysis filter bank (ho (lowpass), go (highpass)) and down-sampled to get the transformed image, which contains the average value and detail coefficients along each row. Next we treat these transformed rows as if they were themselves as image and apply the same process to each column. This transformation process results in four-band (LL, LH, HL, HH) decomposition of an image [12] as shown in fig.1.2.

<table>
<thead>
<tr>
<th>m ≥ 2</th>
<th>m=2</th>
<th>m=1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low resolution sub images (LL2)</td>
<td>Horizontal orientation sub image at m=2 (LH2)</td>
<td>Resolution m=1 Horizontal orientation sub image (LH1)</td>
</tr>
<tr>
<td>Vertical orientation Sub image at m=2 (HL2)</td>
<td>Diagonal orientation sub image at m=2 (HH2)</td>
<td></td>
</tr>
<tr>
<td>Resolution m=1 Vertical orientation sub image at m=2 (HL1)</td>
<td>Resolution m=1 Diagonal orientation sub image (HH1)</td>
<td></td>
</tr>
</tbody>
</table>

Fig.1.2 Image decomposition
Two ways of classifying compression techniques [13] are:

(a) Lossless vs. Lossy compression:

In lossless compression schemes, the reconstructed image is numerically identical to the original image. However lossless compression can only achieve a modest amount of compression.

An image reconstructed using lossy compression techniques, contains degradation relative to the original. This is because the compression scheme completely discards redundant information. However, some lossy schemes are capable of achieving much higher compression.

(b) Predictive vs. Transform coding:

In predictive coding, information already available is used to predict next value, and the difference is encoded. Since this is done in the spatial domain, it is relatively simple to implement and is readily adapted to local image characteristics, e.g. Differential Pulse Code Modulation (DPCM) scheme.

Transform coding, on the other hand, first transforms the image from its spatial domain representation to a different type of representation using well-known transforms and then the transformed coefficients are coded. This method provides greater data compression compared to predictive method, at the expense of greater computation.

Ex: JPEG (Joint Photographic Experts Group).

The JPEG uses, Discrete Cosine Transform (DCT). It is being used for still image compression. In JPEG, quantization and encoding are done using a quantization table, run length encoding (RLE), and Huffman coding. The DCT-based image coders perform very well at moderate bit rates (around 1 bit per pixel),
at higher compression ratios (i.e., at low bit-rates (0.163b/p)), image quality degrades because of the artifacts resulting from the block-based DCT scheme.

Recently Wavelet Transform has emerged as a cutting edge technology, within the field of image compression. Wavelet-based coding provides substantial improvements in picture quality at higher compression ratios using the existence of overlapping basis and high-energy compaction property which tend to put most "energy" of the signal (or image) into a relatively lesser number of coefficients. Because of the inherent multi-resolution nature, wavelet-based coders facilitate progressive transmission of images thereby allowing variable bit rates.

Over the past few years [1] – [55], a variety of schemes for image compression have been developed. Programs developed and discussed in this thesis can be applied to real world signals and images. Images of any form, namely, Joint Photographic Experts Group (JPEG), Portable Network Graphics (PNG), and Graphics Interchange Format (GIF) etc. can be compressed. Among them, are Embedded Zero-tree Wavelet (EZW) and the Set Partitioning in Hierarchical Trees (SPIHT), introduced by Shapiro [14] and Amir Said & Pearlman [15,16]. In this thesis both these algorithms are used for still image compression, which is a lossy compression scheme, and finally an application of this for transmitting information with the image in the form of invisible watermark is proposed using MD5 [17] and Ron Rivest, Adi Shamir and Len Adleman (RSA) algorithms [18]. In this the original intelligible message, is referred to as ciphertext. The encryption process consists of an algorithm and a key. The key is a value independent of the plain text. The algorithm will produce a different output depending on the specific key being used at that time. All forms of cryptanalysis for conventional encryption schemes
are designed to exploit the fact that traces of structure or pattern in the plain text may survive encryption and be discernible in the ciphertext. The methods of Steganography conceal the existence of the message, whereas the methods of cryptography render the message unintelligible to outsiders by various transformations of the text. Diffie and Hellman [19] introduced an approach to cryptography, which challenged the cryptologists to come up with cryptographic algorithm that meets the requirements for public-key systems. After inserting the information to be transmitted in the image, it is compressed for transmission purpose. For recovering the information decompression is performed and reconstructed image is compared with its reference image. The results of all the image compression algorithms are analyzed for compression ratio, Peak Signal to noise Ratio (PSNR) and Mean Square Error (MSE) and are found to be comparable and satisfactory.