Abstract
One of the significant challenges in the present multimedia world is the optimized use of storage space and Bandwidth. The image compression is the only solution. In this paper discrete wavelet Transform is used which is one of the major processing components of image compression. The wavelets transforms implemented here are Haar, Daubechies and Coiflet. Wavelet transformation is a technique that provides information in both spatial and frequency domain. The objective of this paper is to analyse the performance of these transforms in terms of Mean square error (MSE), Peak signal to noise ratio (PSNR), Root mean square error (RMSE) and Compression Ratio (CR).

1. Introduction
Image compression, the art and science of reducing the amount of data required to represent an image is one of the most useful and commercially successful technologies in the field of Digital Image processing [3]. Image compression is important for an efficient transmission and storage of an image. A common characteristic of most images has neighbouring pixels which are highly correlated and contain highly redundant information. The basic component of image compression is used to find an image representation in which pixels are less correlated. The two fundamental principles used in image compression are redundancy and irrelevancy. Redundancy removes redundancy from the signal source and irrelevancy omits pixel values which are not noticeable by human eye.
2. Discrete Wavelet Transform (DWT)

DWT is now used in image compression as it has the capability to provide higher compression ratios with better image quality due to higher de-correlation property. Filter banks are used for the construction of the multi-resolution time-frequency plane. The DWT analyses the signal at different frequency bands with different resolutions by decomposing the signal into an approximation & detail information. The decomposition of the signal into different frequency bands obtained by the successive high-pass g (n) and low-pass h (n) filtering of the time domain signal. The basis of Discrete Cosine Transform (DCT) is cosine functions while the basis of Discrete Wavelet Transform is a wavelet function that satisfies requirement of multi-resolution analysis [9]. Discrete Wavelet Transform processes data on a variable time-frequency plane that matches progressively the lower frequency components to coarser time resolutions and the high-frequency components to finer time resolutions, thus achieving a multi-resolution analysis [8]. The introduction of the DWT made it possible to improve some specific applications of image processing by replacing the existing tools with this new mathematical transform.

The main properties of wavelet functions in image compression are compact support (lead to efficient implementation), symmetry (useful in avoiding de-phasing), orthogonally (allow fast algorithm), regularity & degree of smoothness (related to filter order or filter length) [11]. The compression performance for images with different spectral activity will decides the wavelet function from wavelet family. Daub and Coif wavelets are classes of orthogonal wavelets that are compactly supported. Compactly supported wavelets correspond to finite-impulse response (FIR) filters and thus lead to efficient implementation.

2.1 Wavelet Transforms

2.1.1 Haar wavelet

The Haar wavelet is a sequence of rescaled "square-shaped" functions which together form a wavelet family or basis [12]. The Haar sequence was proposed in 1909 by Alfréd Haar. The Haar wavelet is the simplest possible wavelet. The Haar Transform is one of the simplest and basic transformations from the space domain to a local frequency domain. A HT decomposes each signal into two components, one is called average (approximation) or trend and the other is known as difference (detail) or fluctuation [10]. In Daubechies wavelet, the Haar wavelet is also known as D2.

2.1.2 Daubechies Wavelet

The Daubechies wavelets are a family of orthogonal wavelets defining a discrete wavelet transform and characterized by a maximal number of vanishing moments A for given support width N = 2A. With each wavelet type, there is a scaling function (also called father wavelet) which generates an orthogonal multiresolution analysis. Two naming schemes are used, DN using the length or number of taps, and dbA referring to the number of vanishing moments. So D4 and db2 are the same wavelet transform.

2.1.3 Coiflet Wavelet

Coiflets are discrete wavelets designed by Ingrid Daubechies, at the request of Ronald Coifman to have scaling functions with vanishing moments. The wavelet is near symmetric with wavelet...
functions have N/3 vanishing moments & scaling functions N/3 – 1. These are compactly supported wavelets with highest number of vanishing moments for both phi and psi for a given support width.

3. Research Methodology

Figure below shows the flowchart of Research Methodology which summarizes the way to achieve the desired goal.

- **Algorithm for Compression**
  
  Step 1: Read the original color image.
  Step 2: Convert the original color into gray scale image.
  Step 3: Apply 2D DWT (haar, daub2, daub3 and coif1) to perform compression.
  Step 4: Obtain the compressed image.
  Step 5: stop

- **Algorithm for Decompression**
  
  Step 1: Input the compressed Image.
  Step 2: Apply Inverse DWT (haar, daub2, daub3 and coif1) on compressed image.
  Step 3: Obtain the decompressed image.
  Step 4: stop
4. Results And Discussion

We have taken three test images. The coding for the work is done in MATLAB. Figure below shows the three test Images.

![Image of three test Images](image1.jpg)

**Figure 4.1:** (a) Original Lena Image (b) Original Peppers Image (c) Original Baboon Image

### 4.1.1 Compression and Decompression

The compression & decompression is performed on the three test images using haar, daub2, daub3 and coif1 wavelet filter. The compression and decompression results for different Wavelet Techniques are shown below. The degradation in the original image is measured by comparing reconstructed and Original images. The degradation results for the different Wavelet Techniques are also shown below.

![Image of compressed Lena Images](image2.jpg)

**Figure 4.1.1:** Original & Compressed Lena Images
Figure 4.1.2: Original & Reconstructed Lena Images using various Wavelet Techniques

Figure 4.1.3: Degraded Images
Er. Rupinder Kaur, Dr. Jagroop Singh :: Discrete Wavelet Transform For Image Compression And Quality Assessment Of Compressed Images
Er. Rupinder Kaur, Dr. Jagroop Singh :: Discrete Wavelet Transform For Image Compression And Quality Assessment Of Compressed Images

Figure 4.1.6: Degraded Images

Figure 4.1.7: Original & Compressed Baboon Images
Er. Rupinder Kaur, Dr. Jagroop Singh :: Discrete Wavelet Transform For Image Compression And Quality Assessment Of Compressed Images

4.2 Performance Evaluation for Test Images
The performance evaluation for the Test Images is done on the basis of Mean Square Error (MSE), Peak Signal to Noise Ratio (PSNR), Compression Ratio (CR), and RMSE. The results in tabular form and in bar graphs are shown below:

Table 4.2.1: MSE, PSNR, CR & RMSE Comparison for LENA.JPG using different Wavelet Techniques

<table>
<thead>
<tr>
<th>Wavelet Filters</th>
<th>MSE</th>
<th>PSNR</th>
<th>CR</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Haar</td>
<td>178.5236</td>
<td>25.6138</td>
<td>119.2700</td>
<td>13.3613</td>
</tr>
<tr>
<td>Daub2</td>
<td>2.0824e+003</td>
<td>14.9452</td>
<td>136.1345</td>
<td>45.6331</td>
</tr>
<tr>
<td>Daub3</td>
<td>5.4136e+003</td>
<td>10.7959</td>
<td>0.3286</td>
<td>73.5772</td>
</tr>
<tr>
<td>Coif1</td>
<td>8.6301e+003</td>
<td>8.7706</td>
<td>146.9922</td>
<td>92.8985</td>
</tr>
</tbody>
</table>

Figure 4.1.8: Original & Reconstructed Peppers Images using various Wavelet Techniques

Figure 4.1.9: Degraded Images
Figure 4.2.1: (a) MSE for Lena Image (b) PSNR for Lena Image (c) RMSE for Lena Image (d) CR for Lena Image

Table 4.2.2: MSE, PSNR, CR & RMSE Comparison for PEPPERS. JPG using different Wavelet techniques

<table>
<thead>
<tr>
<th>Wavelet Filters</th>
<th>MSE</th>
<th>PSNR</th>
<th>CR</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Haar</td>
<td>143.6450</td>
<td>26.5579</td>
<td>121.0790</td>
<td>11.9852</td>
</tr>
<tr>
<td>Daub2</td>
<td>2.1210e+003</td>
<td>14.8654</td>
<td>136.9258</td>
<td>46.0540</td>
</tr>
<tr>
<td>Daub3</td>
<td>5.0508e+003</td>
<td>11.0972</td>
<td>0.3278</td>
<td>71.0692</td>
</tr>
<tr>
<td>Coif1</td>
<td>8.3890e+003</td>
<td>8.8937</td>
<td>147.5320</td>
<td>91.5913</td>
</tr>
</tbody>
</table>

Figure 4.2.2: (a) MSE for Peppers Image (b) PSNR for Peppers Image (c) RMSE for Peppers Image (d) CR for Peppers Image
Table 4.2.3 MSE, PSNR, CR & RMSE Comparison for BABOON.JPG using different Wavelet Techniques

<table>
<thead>
<tr>
<th>Wavelet Filters</th>
<th>MSE</th>
<th>PSNR</th>
<th>CR</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Haar</td>
<td>63.3516</td>
<td>30.1132</td>
<td>123.4451</td>
<td>7.9594</td>
</tr>
<tr>
<td>Daub2</td>
<td>2.0114e+003</td>
<td>15.0957</td>
<td>142.0138</td>
<td>44.8491</td>
</tr>
<tr>
<td>Daub3</td>
<td>5.4207e+003</td>
<td>10.7902</td>
<td>0.3312</td>
<td>73.6254</td>
</tr>
<tr>
<td>Coif1</td>
<td>9.1643e+003</td>
<td>8.5098</td>
<td>153.2492</td>
<td>95.7306</td>
</tr>
</tbody>
</table>

Figure 4.2.2: (a) MSE for Baboon Image (b) PSNR for Baboon Image (c) RMSE for Baboon Image (d) CR for Baboon Image

5. Conclusion And Future Scope

Nowadays image compression is being used in order to reduce the memory required to store the images. In this dissertation different wavelet transforms has been used to compress the image and reconstruct the original image. DWT technique is used for obtaining the desired results. Different wavelets are used at 1st level of decomposition and comparative analysis of Haar, Daub and coif family are displayed. Quantitative analysis has been presented by measuring the values of attained Peak Signal to Noise Ratio and Compression Ratio, MSE and RMSE at 1st decomposition levels. Qualitative analysis has been performed by obtaining the compressed version of the input image by DWT Technique and comparing it with the test image. Our results shows that Haar, Daub and Coif wavelet gives better result in each family. On the basis of compression ratio and MSE it has been find out that the best compression and
reconstruction of the image can be done using HAAR wavelet transform and Coif1 provides best results in terms of Compression Ratio. Further Steps that can be taken in future are

- Some higher level of Wavelet Transforms can be implemented for Daubechies (daub4, daub5.) and Coiflet (coif2..coif5) to see how increase in no. of Scaling and Wavelet Coefficients affect the Compression of an Image.
- No. of decomposition levels can be increased.
- Some latest techniques such as Neural network and fuzzy logic can be used. The neural network is used to compress and decompress the image to achieve the reliable space and reduce the complexity of the calculation and computation values.

References