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Image Compression Using Morphological Wavelet Transform

a dissertation submitted in partial fulfilment of the requirements for the M. Tech. (Computer Science) degree of the Indian Statistical Institute

By

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A THESIS

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Certificate of Approval

This is to certify that this dissertation thesis titled "Image Compression Using Morphological Wavelet Transform" submitted by Ms. Parul Kapoor in partial fulfillment of the requirements for the M. Tech. (Computer Science) degree of the Indian Statistical Institute, Kolkata, embodies the work done under my supervision.

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Parul Kapoor
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Abstract

A technique to compress an image is described here.
The image compression includes transform of image, quantization and encoding. For the transform of image a multiresolution signal decomposition scheme is used, which is based on a nonlinear wavelet constructed with morphological operators. Analysis Operators are constructed with morphological dilation combined with quadratic downsampling and the Synthesis Operators are constructed with morphological erosion combined with quadratic upsampling. Quantization is done by taking a threshold value. For the encoding purpose, EZW algorithm is used which has the property that bits in the bit stream are generated in order of their importance. On the bit stream obtained further Arithmetic Encoder is aaplied.
The experiments are performed on six images. A performance measure based on PSNR is used to evaluate the results.

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Chapter 1
Introduction

Images are being extensively used in every sphere of our life. Apart from overwhelming influence of television, common people look for images in newspapers, advertisements, item catalogues, entertainment, education, architecture, painting and many others. Professionals use image in criminology (e.g., fingerprint identification, face recognition), medicine (e.g., case-based diagnosis from radiographs or scan data),fashion design, historical archiving, fine arts and so on. In many cases it is the case that in general a large size image has to be transmitted from one channel to another. Such transmission can cause high cost and huge memory. To overcome this problem images are compressed to smaller size. Once the images are compressed the process of transmission and storage becomes easier and bears less cost.
In this chapter we discuss about what exactly is Image Compression and what kind of redundancies need to be eliminated to achieve compression.

Image compression is minimizing the size in bytes of a graphics file without degrading the quality of the image to an unacceptable level. The reduction in file size allows more images to be stored in a given amount of disk or memory space. It also reduces the time required for images to be sent over the Internet or downloaded from Web pages.
In effect, the objective is to reduce redundancy of the image data in order to be able to store or transmit data in efficient form.

1.1 Types Of Redundancies

1. Statistical Redundancy
2. Psychovisual Redundancy

1.1.1 Statistical Redundancy

Statistical Redundancy can be further classified into two types:

- Interpixel Redundancy
- Coding Redundancy

1.1.1 (a) Interpixel Redundancy:

It means that the pixels of an image are not statistically independent. They are correlated to various degrees. Usually the value of certain pixel in the image can be reasonably predicted from the values of group of other pixels in the image. For example the gray levels of neighboring pixels are roughly the same and by knowing gray level value of one of the neighborhood pixels one has a lot of information about gray levels of other neighborhood pixels. Thus the value of the individual pixel carries relatively small amount of information and much more information about pixel value can be inferred on the basis of its neighbors' values. These dependencies between pixels' values in the image are called ***interpixel redundancy***.

1.1.1(b) Coding Redundancy:

By ***Coding Redundancy*** we mean the statistical redundancy associated with the coding techniques. It has nothing to do with information redundancy but with the representation of information, i.e., coding itself. Sometimes for the same set of symbols different codes may perform differently. Some may be efficient than others.

In general coding redundancy is present in an image if the possible values are coded in such way that they use more code symbols that absolutely necessary.

From the study of coding redundancy, it is clear that we should search for more efficient coding techniques in order to compress image data.

1.1.2 Psychovisual Redundancy

It is known that the human eye does not respond to all visual information with equal sensitivity. Some information is simply of less relative importance. This information is referred to as psychovisual redundant and can be eliminated without introducing any significant difference to the human eye. The reduction of redundant visual information has some practical applications in image compression.

1.2. Different Classes For Image Compression Techniques

There are two ways of classifying compression techniques.

- Lossless vs. Lossy Compression
- Predictive vs. Transform Coding

1.2.1 Lossless vs. Lossy Compression:

In lossless compression schemes, the reconstructed image, after compression, is numerically identical to the original image. However lossless compression can only achieve a modest amount of compression. An image reconstructed following lossy compression contains degradation relative to the original. Often this is because the compression scheme completely discards redundant information. However, lossy schemes are capable of achieving much higher compression.

1.2.2 Predictive vs. Transform Coding:

In predictive coding, information already sent or available is used to predict future values, and the difference is coded. Since this is done in the image or spatial domain, it is relatively simple to implement and is readily adapted to local image characteristics. Differential Pulse Code Modulation (DPCM) is one particular example of predictive coding. Transform coding, on the other hand, first transforms the image from its spatial domain representation to a different type of representation using some well-known transform and then codes the transformed values (coefficients). This method provides greater data compression compared to predictive methods, although at the expense of greater computation.

1.3. Typical Model For Image Compression

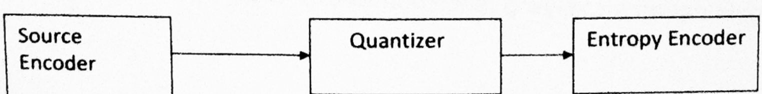
A typical lossy image compression system consists of three closely connected components namely

(a) Source Encoder

(b) Quantizer

(c) Entropy Encoder

Compression is accomplished by applying a linear transform to decorrelate the image data, quantizing the resulting transform coefficients, and entropy coding the quantized values.



Chapter 2
Morphological Wavelet Transform

Before we discuss about the Morphological Wavelet Transform that we used in this project for Image Compression, it becomes almost mandatory for us to discuss the Multiresolution Signal Decomposition.
So first we'll discuss about the multiresolution signal decomposition theory using wavelets.

2.1 Multiresolution Analysis

An image often contains physically relevant features at many different scales or resolutions. Multiscale and multiresolution approaches provide a means to exploit this fact. This is one of the reasons why these techniques have become so popular. Multiscale methods involve processing and storing of scaled data at various levels.
The basic idea in these techniques is to decompose the source images at first by applying the wavelet transform, then the further operations for compression are performed on the transformed images and finally the compressed image is reconstructed by inverse transform.
One major advantage of multiresolution transform is that *spatial* as well as *frequency* domain localization of an image is obtained simultaneously. Another advantage is that it can provide information on the sharp contrast changes, and human visual system is especially sensitive to these changes.

The theory of multiresolution signal decomposition scheme using wavelets can be applied to a wide variety of signals. We are restricted here to two-dimensional gray-scale image signals only.

A two-dimensional gray-scale image signal X is a function which map (a subset of) discrete two-dimensional space Z^2 to a finite set of non-negative integers $G=\{g_1,g_2,\ldots,g_n\}$ called the set of gray values.

Let us consider a set V_0 of such image signals. A multiresolution signal decomposition scheme on V_0 uses two types of operators, namely,

- *signal analysis* operators
- *signal synthesis* operators.

Signal analysis operators,

$$\psi_j^{\uparrow} : V_j \longrightarrow V_{j+1}$$

map the signal space Vj at level *j*, to a coarser signal space Vj+1 .

The *detail analysis* operators,

$$\omega_j^{\uparrow} : V_j \longrightarrow W_{j+1}$$

map Vj to a coarser detail space W_{j+1}

All Vj s and Wjs have the same structure as V_0.

The operators $\psi_j^{\uparrow}$ and $\omega_j^{\uparrow}$ are called the *scaling function* and the *wavelet function*, respectively.

Signal analysis operation proceeds by mapping a signal to a level higher in the pyramid structure, thereby reducing information. Details are stored at each level to restore this information loss.

So, for

$X_j \in V_j$ we have,

$$\psi_j^{\uparrow}(X^j) = X^{j+1} \quad , X^{j+1} \varepsilon \; V_{j+1},$$

$$\omega_j^{\uparrow}(X^j) \;=\; Y^{j+1} \;, Y^{j+1} \varepsilon \; W_{j+1}.$$

Signal synthesis or reconstruction is done by *synthesis operator,*

$$\psi_j^{\downarrow} \; : V_{j+1} \;\; \mathrm{x} \;\; W_{j+1} \longrightarrow V_j$$

which map a signal to a level lower in the pyramid. To ensure *loss-less* or *perfect reconstruction*, the following condition must be satisfied.

$$\psi_j^{\downarrow} \left(\psi_j^{\uparrow} (X^j),\, \omega_j^{\uparrow}(X^j)\right) = X^j \quad , \quad X^j \,\varepsilon\, V_j$$

2.2. Morphological operators

A brief overview of the morphological operators is given now. Let us consider a signal $X \in V_0$. So X is a function from domain D to G where D is a subset of $Z2$ and G is the set of gray-values. Let $A \subset Z^2$ be a *structuring element*. Then the morphological operators, *dilation* $\delta A(X)$ and *erosion* $\varepsilon A(X)$ of X by A are defined as

$$\delta_A(X)(r,c) = \max_{(r',c') \in A,\,(r-r',c-c') \in D} X(r-r',c-c'),$$

$$\varepsilon_A(X)(r,c) = \min_{(r',c') \in A,\,(r+r',c+c') \in D} X(r+r',c+c')$$

So *dilation* (*erosion*) simply replace the value at each point of X by the maximum (minimum) value in a neighborhooddefined by the *structuring element A.*

2.3 Morphological Wavelet

We, now discuss a *morphological wavelet* decomposition scheme, which will be used for my image-compression algorithm. Unique *analysis* operators $(\psi^{\uparrow},\omega^{\uparrow})$ are used at all levels of the multiresolution scheme. Similarly, unique *synthesis* operators $(\psi^{\downarrow},\omega^{\downarrow})$ are used at all levels.

Here the operators are explained for the lowermost levels 0 and 1.

Let us consider the signal space V_0.

It is the original signal space. Then V_1 and W_1 are the signal and detail spaces at level 1 having the same structure as V_0.

Consider an image signal $X \in V_0$. Then X is a mapping of (a subset of) Z^2 to the set of gray-values G and it can be represented by an $M \times N$ matrix, where $M,N \in Z$.

Let us assume that M and N both are even. Then X can be divided into consecutive and disjoint 2×2 sub matrices or blocks, which are total $MN/4$ in number.

For positions of such a block B may be denoted by (r,c), $(r,c+1)$, $(r+1,c)$ and $(r+1,c+1)$.

Using quadratic down sampling, the ***analysis operators*** $\psi^{\uparrow}:V_0\rightarrow V_1$ and $\omega^{\uparrow}:V_0\rightarrow W_1$ are defined as

$$\psi^{\uparrow}(X)(B) = M = \max\{X(r,c), X(r,c+1), X(r+1,c), X(r+1,c+1)\},$$

$$\omega^{\uparrow}(X)(B) = (y_v, y_h, y_d),$$

where y_v, y_h, y_d represent the *vertical*, *horizontal* and *diagonal* detail signals, respectively.

Vertical Detail Signal is defined as

$$y_v = \begin{cases} M - X(r,c+1) & \text{if } M - X(r,c+1) > 0, \\ X(r,c+1) - M & \text{otherwise.} \end{cases}$$

Horizontal Detail Signal is defined as

$$y_h = \begin{cases} M - X(r,c+1) & \text{if } M - X(r,c+1) > 0, \\ X(r,c+1) - M & \text{otherwise,} \end{cases}$$

Diagonal Detail Signal is defined as

$$y_d = \begin{cases} M - X(r+1,c+1) & \text{if } M - X(r+1,c+1) > 0, \\ X(r-1,c+1) - M & \text{otherwise.} \end{cases}$$

Scaled signal and detail values obtained above belong to X1 and Y1, respectively, and they can be stored conveniently in similar positions of another matrix.

Using quadratic down sampling, *synthesized signals,* $\dot{X}$ are given by

$$\dot{X}(r,c) = \dot{X}(r,c+1) = \dot{X}(r+1,c) = \dot{X}(r+1,c+1) = M$$

and *synthesized details* are given by

$$\dot{Y}(r,c) = \min(y_v, y_h, y_d, 0),$$

$$\dot{Y}(r,c+1) = \min(y_v, 0),$$

$$\dot{Y}(r+1,c) = \min(y_h, 0),$$

$$\dot{Y}(r+1,c+1) = \min(y_d, 0).$$

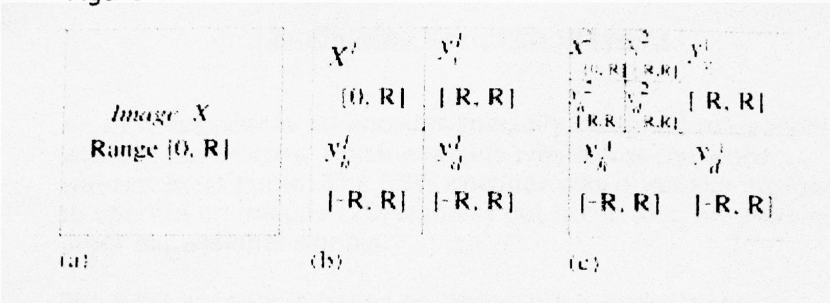
Hence the ***reconstructed signal*** X′ at any point (u,v)∈{(r,c),(r,c+1),(r+1,c),(r+1,c+1)} is given by

$$X'(u,v) = X(u,v) + Y(u,v).$$

where binary operation $+$ is the ordinary addition of numbers.

The analysis operator-pair can be used recursively to decompose a signal up to a desired level $k \geq 1$. Similarly the synthesis operator-pair can be used recursively to reconstruct a signal from any level to the lowest level 0. It is easy to see that the analysis and synthesis operators satisfy the perfect reconstruction and non-redundancy conditions. The analysis operators $\psi^{\uparrow}$ and $\omega^{\uparrow}$ involve simple arithmetic operations and one interesting point to note is that the integer values are mapped to integer values only. Another point to note is that, if all values of X belong to the range $[0,R]$, then analyzed signal-values will belong to the range $[0,R]$ and analyzed detail-values will belong to the range $[-R,R]$, irrespective of the number of times the operators are applied .

Figure 2.1.



In Figure 2.1.

(a) Original signal *X*

(b) scaled signal X^1 and details $Y^1 = \{y_v^1, y_h^1, y_d^1\}$ at level 1

(c) scaled signal X^2 and details Y2 = $\{y_v^2, y_h^2, y_d^2\}$ at level 2.

Chapter 3

Embedded Zerotree Wavelet

An EZW encoder is an encoder specially designed to use with *wavelet transforms*, which explains why it has the word wavelet in its name. The EZW encoder was originally designed to operate on images (2D-signals) but it can also be used on other dimensional signals.

The EZW encoder is based on *progressive encoding* to compress an image into a bit stream with increasing accuracy . Progressive encoding is also known as *embedded encoding*, which explains the E in EZW.

A zerotree is a quad-tree of which all nodes are equal to or smaller than the root. The tree is coded with a single symbol and reconstructed by the decoder as a quad-tree filled with zeroes.
Zerotree coding which provides a compact multiresolution representation of *significance maps,* which are binary maps indicating the positions of the significant coefficients. Zerotrees allow the successful prediction of insignificant coefficients across scales to be efficiently represented as part of exponentially growing trees.

In general images have a low pass spectrum. When an image is wavelet transformed the energy in the subbands decreases as the scale decreases (low scale means high resolution), so the wavelet coefficients will, on average, be smaller in the higher subbands than in the lower subbands. Because of this reason progressive encoding is chosen for compressing wavelet transformed images, since the higher subbands only add detail.

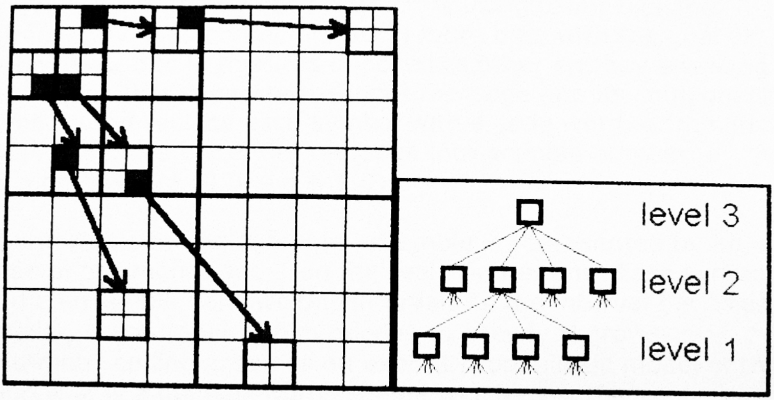
In EZW encoder the wavelet coefficients are encoded in decreasing order, in several passes. For every pass a threshold is chosen against which all the wavelet coefficients are measured. If a wavelet coefficient is larger than the threshold it

is encoded and removed from the image, if it is smaller it is left for the next pass. When all the wavelet coefficients have been visited the threshold is lowered and the image is scanned again to add more detail to the already encoded image. This process is repeated until all the wavelet coefficients have been encoded completely.
The dependency between the wavelet coefficients across different scales here is used to efficiently encode large parts of the image which are below the current threshold.

After wavelet transforming an image we can represent it using trees because of the sub sampling that is performed in the transform. A coefficient in a low subband can be thought of as having four descendants in the next higher subband. The four descendants each also have four descendants in the next higher subband and we see a *quad-tree* emerge: every root has four leafs. The root has to be smaller than the threshold against which the wavelet coefficients are currently being measured.

The EZW encoder exploits the zerotree based on the observation that wavelet coefficients decrease with scale. It assumes that there will be a very high probability that all the coefficients in a quad tree will be smaller than a certain threshold if the root is smaller than this threshold. If this is the case then the whole tree can be coded with a single zerotree symbol.

Figure 3.1.



The relation between wavelet coefficients in different subbands as quad-trees is shown in Figure 4.1.

Chapter 4
Arithmetic coding

Arithmetic coding is a method for lossless data compression. Arithmetic coding is a form of variable length entropy encoding that converts a string into another representation that represents frequently used characters using fewer bits and infrequently used characters using more bits, with the goal of using fewer bits in total. As opposed to other entropy encoding techniques that separate the input message into its component symbols and replace each symbol with a code word, arithmetic coding encodes the entire message into a single number, a fraction n where ($0.0 \le n < 1.0$).

In arithmetic coding a source ensemble is represented by an interval between 0 and 1 on the real number line. Each symbol of the ensemble narrows this interval. As the interval becomes smaller, the number of bits needed to specify it grows. Arithmetic coding assumes an explicit probabilistic model of the source. It is a defined-word scheme which uses the probabilities of the source messages to successively narrow the interval used to represent the ensemble. A high probability message narrows the interval less than a low probability message, so that high probability messages contribute fewer bits to the coded ensemble. The method begins with an unordered list of source messages and their probabilities. The number line is partitioned into subintervals based on cumulative probabilities.

Arithmetic Decoding

In order to recover the original ensemble, the decoder must know the model of the source used by the encoder (eg., the source messages and associated ranges) and a single number within the interval determined by the encoder. Decoding consists of a series of comparisons of the number i to the ranges representing the source messages. This process continues until the entire ensemble has been recovered.

The **algorithm** to implement **Arithmetic Encoding** for any message of any length is is shown below:

```
Set low to 0.0
Set high to 1.0
While there are still input symbols do
    get an input symbol
    code_range = high - low.
    high = low + range*high_range(symbol)
    low = low + range*low_range(symbol)
End of While
output low
```

where the range is decided by knowing the probabilities of the occurrence of the symbol

The **algorithm** for **Decoding** the incoming number looks like this:

```
get encoded number
Do
    find symbol whose range straddles the encoded number
    output the symbol
    range = symbol low value - symbol high value
    subtract symbol low value from encoded number
    divide encoded number by range
until no more symbols
```

Chapter 5

Methodology Adopted In This Project For Image Compression

As we have seen earlier that while compressing an image there are three major processes to be done. They are:

1. Source Encoding
2. Quantization
3. Entropy Encoding
4. Decoding
5. Dequantization

Initially a 256x256 grayscale image is taken which is used as the input image, on which this whole compression algorithm is applied.

The method is used on six images in all.

5.1. Source Encoding

In this project for Source Encoding, transform coding will be done, for which the Morphological Wavelet Transform is used whose theory is discussed earlier in Chapter 2.

5.1.1 Implementation Of Morphological Wavelet Transform

While discussing the theory of the Morphological Wavelet that is used in this project the concept of signal analysis operators and the signal synthesis operator is explained.

To implement the discussed Morphological Wavelet on the given input image, say X, the whole image X was divided into 2x2 blocks. As the image size is 256x256 we get 32,768 number of blocks.

Once we get 2x2 blocks, the analysis operators $\psi^{\uparrow}$ and $\omega^{\uparrow}$ discussed in Chapter 2 are applied on these blocks. In this manner all the values in each block of image X is replaced by a new value X^1.

$$X^1(r,c) = M = \max\{X(r,c), X(r,c+1), X(r+1,c), X(r+1,c+1)\},$$

$$Y^1(r,c+1) = y_v$$

$$y_v = \begin{cases} M - X(r,c+1) & \text{if } M - X(r,c+1) \geq 0, \\ X(r,c+1) - M & \text{otherwise.} \end{cases}$$

$Y^1(r+1,c) = y_h$

$$y_h = \begin{cases} M - X(r,c+1) & \text{if } M - X(r,c+1) \geq 0, \\ X(r,c+1) - M & \text{otherwise.} \end{cases}$$

$Y^1(r+1,c+1) = y_d$

$$y_d = \begin{cases} M - X(r+1,c+1) & \text{if } M - X(r+1,c+1) \geq 0, \\ X(r+1,c+1) - M & \text{otherwise.} \end{cases}$$

To view the result sensibly, all the top left components of the 2x2 blocks have been grouped together to form the *scaled* image (on the top left in Figure 5.1), similar process is done with other 3 positions to get the images that contain the *vertical details*(top right in Figure5.1), *horizontal details*(bottom left in Figure2.1) and *diagonal details* (bottom right in Figure5.1) of the original image X.

Figure5.1

This transform is applied up to 3 levels of subband decomposition.

5.2. Quantization

Once we get the transformed image after applying the above Morphological Wavelet, say we get image X', quantization is applied on it.

All the loss in information that takes place while compressing the image occurs at the quantization stage.

In this project the quantization is done by setting a threshold value, say T. All the pixels in the transformed image X' are divided by the threshold value T and then truncated to the nearest integer value.

For this project results are taken for threshold values 2, 5, 10, 15 and 20.

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In this project the quantization is done by setting a threshold value, say T. All the pixels in the transformed image X' are divided by the threshold value T and then truncated to the nearest integer value.

For this project results are taken for threshold values 2, 5, 10, 15 and 20.

If the coefficient is smaller than the threshold but is not a root of a zerotree, then a symbol Z is coded.

After this all the coefficients that in absolute value are greater than the current threshold are extracted and placed without their sign in the subordinate list and their position in image is replaced by zeros.

In the subordinate pass a new threshold is found by dividing the current threshold by 2. It is done till the threshold value is 1.For all the elements in the subordinate list, if the coefficient is greater than the new found threshold then 1 is outputted and then coefficient is updated as coefficient-new threshold. If the coefficient is less than the new found threshold then 0 is outputted.
Once we get a string of 0's and 1's after the subordinate pass, the arithmetic encoder is applied on that string to obtain the encoded version of the image.

5.4 Decoding

Once we get the encoded version of the image, our next step is to decode the encoded version.
First we apply the Arithmetic Decoder on the encoded version of the image.
For EZW decoding we have a string of symbols, for all the levels we take a matrix of zeros of the size of the image which was coded.
If a symbol P is found then the threshold value is checked, if it is 1 then the corresponding position in the matrix of zeros is replaced by threshold value else by the value which is 1.5 times the threshold value.

Similarly if a symbol N Is found then the threshold value is checked, if it is 1 then the corresponding position in the matrix of zeros is replaced by negative of the threshold value else by the value which is -1.5 times the threshold value.

If a symbol T Is found then all zerotree descendants are set to 1.

In this manner the decoding of the symbols is done so as to obtain the reconstructed image.

5.5 Dequantization

In the image obtained after Decoding process we multiply the all the pixel values by the corresponding threshold values taken during the Quantization so as to minimize the error.

5.6 Inverse Wavelet Transform

When we have the reconstructed image that we obtained by decoding the encoded symbols. Our next step is to apply the inverse of the wavelet transform we used so that we can obtain the final compressed image.

For this we divide the reconstructed image into 2x2 blocks and apply the synthesis operators that we discuss in the Chapter 2 related to the Morphological Wavelet Transform.

Using quadratic down sampling, *synthesized signals,* $\dot{X}$ are given by

$$\dot{X}(r,c) = \dot{X}(r,c+1) = \dot{X}(r+1,c)$$
$$= \dot{X}(r+1,c+1) = M$$

Chapter 6

Results and Conclusion

The technique used in this project for Image Compression gives the results with the images with high PSNR values leading to the fact that reconstructed images are of good quality. The compression ratio obtained is also quite significant.

Results Obtained For Lena Image

Threshold Value	PSNR	Compression Achieved
2	52.3797	5.251bpp
5	41.8332	2.9125bpp
10	35.5929	1.6625bpp
15	32.1886	1.125bpp
20	29.8025	0.8175bpp

Original Image

Reconstructed Image With Threshold Value 20

Results Obtained For Plane Image

Threshold Value	PSNR	Compression
2	52.3783	3.85bpp
5	42.1307	2.0625bpp
10	36.0338	1.2875bpp
15	32.5620	0.9575bpp
20	30.0790	0.75625bpp

Original Image

Reconstructed Image With Threshold Value 20

Results Obtained For Clown Image

Threshold Value	PSNR	Compression
2	52.3686	5.775bpp
5	41.8219	3.65bpp
10	35.3557	2.0125bpp
15	31.8535	1.3bpp
20	29.4544	0.93625bpp

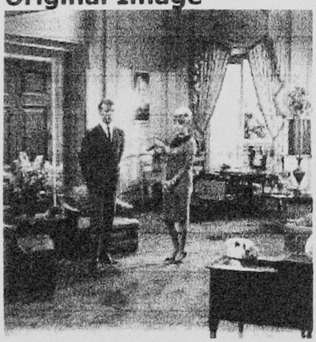
Original Image

Reconstructed Image With Threshold Value 20

Results Obtained For Couple Image

Threshold Value	PSNR	Compression
2	52.4567	5.8375bpp
5	41.7034	3.3875bpp
10	35.3426	1.95bpp
15	31.9794	1.2625bpp
20	29.5656	0.92125bpp

Original Image



Reconstructed Image With Threshold Value 20

Results Obtained For Cameraman Image

Threshold Value	PSNR	Compression
2	52.3979	4.7125bpp
5	41.8245	2.725bpp
10	35.6785	1.65bpp
15	32.2345	1.1575bpp
20	29.7543	0.89625bpp

Original Image

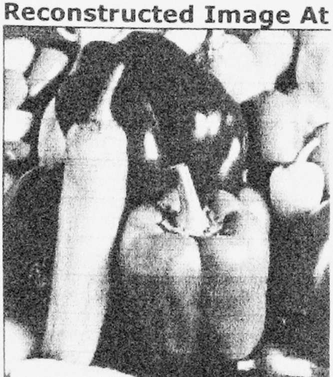
Reconstructed Image With Threshold Value 20

Results For Pepper Image

Threshold Value	PSNR	Compression
2	52.4038	4.1125bpp
5	42.3217	2.2625bpp
10	36.0380	1.3bpp
15	35.9375	0.9225bpp
20	30.1310	0.705bpp

Original Image

Reconstructed Image At Threshold Value 20



Comparison Of The PSNR values and bpp of the **Proposed Method** (Threshold Value 20) with the **JPEG** method

Images	Proposed Method(Threshold Value 20)		JPEG	
	PSNR	bpp	PSNR	bpp
Lena	29.8025	0.8175	36.0523	1.7375
Plane	30.0790	0.75625	25.9445	1.7
Clown	29.4544	0.93625	36.1955	1.8375
Couple	29.5656	0.92125	34.9269	1.9625
Cameraman	29.7543	0.89625	27.0067	1.85
Pepper	30.1310	0.705	32.875	1.815

The results obtained by the experiment carried on using the compression technique used in this project is clearly better than the JPEG technique for four out of six images.

So the work done in this project uses a non-linear wavelet constructed by morphological operators for image compression. The results obtained after its application are quite impressive.

Chapter 7

References

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