# COMBINATION OF LOSSY AND LOSSLESS FOR IMAGE COMPRESSION

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## Abstract

Image compression is a fast paced and dynamically changing field with many different varieties of compression methods available. Images contain large amount of data hidden in them, which is highly correlated. A common characteristic of most images is that the neighboring pixels are correlated and therefore contain redundant information. This research presents an algorithm for image compression consist of a combination of lossy and lossless methods which based on a discrete wavelet transform and apply entropy coding as a lossless compression with using a quantization and thresholding techniques to produce a high compression ratio and high quality of image. Two images (.bmp format) of (256×256) pixels were used as samples to test the algorithm. Experimental results were estimated using the peak signal-to-noise ratio (PSNR) which considered as a measurement to test the quality of reconstructed images samples.

**Keywords:** DWT (discrete wavelet transform), DCT (discrete cosine transform), RLE (Run length encoding), RLD (Run length decoding), PSNR peak signal to noise ratio

## Introduction

Compression refers to reducing the quantity of data used to represent a file, image or video content without excessively reducing the quality of the original data. Image compression is the application of data compression on digital images. The main purpose of image compression is to reduce the redundancy and irrelevancy present in the image, so that it can be stored and transferred efficiently. The compressed image is represented by less number of bits compared to original. Hence, the required storage size will be reduced, consequently maximum images can be stored and it can transferred in faster way to save the time, transmission bandwidth.

For this purpose many compression techniques i.e. scalar/vector quantization, differential encoding, predictive image coding, transform

coding have been introduced. Among all these, transform coding is most efficient especially at low bit rate. Depending on the compression techniques the image can be reconstructed with and without perceptual loss. In lossless compression, the reconstructed image after compression is numerically identical to the original image. In lossy compression scheme, the reconstructed image contains degradation relative to the original. Lossy technique causes image quality degradation in each compression or decompression step. In general, lossy techniques provide for greater compression ratios than lossless techniques i.e. Lossless compression gives good quality of compressed images, but yields only less compression whereas the lossy compression techniques lead to loss of data with higher compression ratio. The approaches for lossy compression include lossy predictive coding and transform coding. Transform coding, which applies a Fourier-related transform such as DCT and Wavelet Transform such as DWT are the most commonly used approach [1].

From last few decays, the increasing demand of storage and transmission of digital images, image compression is now become an essential application for storage and transmission. Demand for communication of multimedia data through the telecommunications network and accessing the multimedia data through Internet is growing explosively. With the use of digital cameras, requirements for storage, manipulation, and transfer of digital images, has grown explosively [2].

Image compression also plays a critical role in telematics applications. It is desired that either single images or sequences of images be transmitted over computer networks at large distances so as that they could be used for a multitude of purposes. For instance, it is necessary that medical images be transmitted so as that reliable, improved and fast medical diagnosis performed by many centers could be facilitated. To this end, image compression is an important research issue. The difficulty, however, in several applications lies on the fact that, while high compression rates are desired, the applicability of the reconstructed images depends on whether some significant characteristics of the original images are preserved after the compression process has been finished [3].

## Literatures review

Among the large number of published articles that concerned with designing and building software tools for image compression, it was chosen the following:

1. Bhonde Nilesh, Shinde Sachin, Nagmode Pradip & D.B. Rane (2013) in paper " Image Compression Using Discrete Wavelet Transform " presents an approach towards implemention of the Discrete Wavelet

Transform (DWT) for image compression. The design follows the JPEG2000 standard and can be used for both lossy and lossless compression [3].

2. Miss. S.S. Tamboli & Dr. V. R. Udupi (2013) in paper " Image Compression using Haar wavelet transform" proposes a simple scheme for 2D-Haar wavelet transformation in image compression. The proposed work is aimed at developing computationally efficient and effective algorithms for lossy image compression using wavelet techniques. The work is particularly targeted towards wavelet image compression using Haar Transformation with an idea to minimize the computational requirements by applying different compression thresholds for the wavelet coefficients [9].

**Objective of research**

The objective of this paper is to build a software for image compression consist of a combination of lossy and lossless methods which based on a discrete wavelet transform and apply entropy coding as a lossless compression with using a quantization and thresholding techniques to produce a high compression ratio and high quality of image.
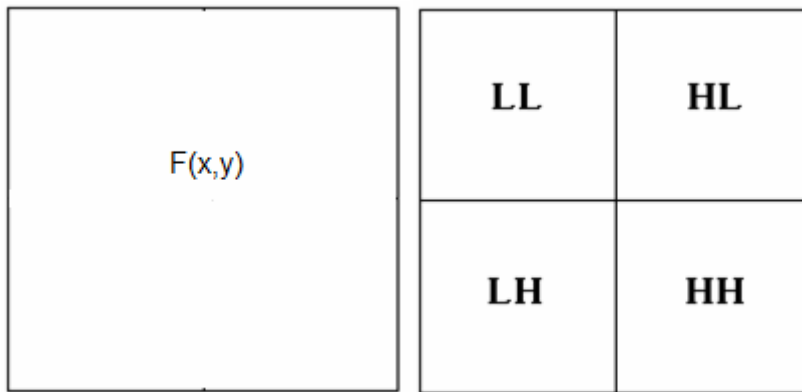
**The wavelet transform**

The wavelet transform is a method of converting a function (or signal) into another form which either makes certain features of the original signal more amenable to study or enables the original data set to be described more succinctly. Wavelets are functions generated from a single basis function by its operations dilations and translations. Wavelets are used in applications such as computer graphics, image compression and digital image processing and feature detection [4] &[ 5].

An image is represented as a two dimensional array of coefficients, each coefficient representing the brightness level in that point. Most natural images have smooth color variations, with the fine details being represented as sharp edges in between the smooth variations. Technically, the smooth variations in color can be termed as low frequency components and the sharp variations as high frequency components. The low frequency components (smooth variations) constitute the base of an image, and the high frequency components (the edges which give the detail) add upon them to refine the image, thereby giving a detailed image. Therefore, the smooth variations are demanding more importance than the details [6].

Separating the smooth variations and details of the image can be done in many ways. One such way is the decomposition of the image using a Discrete Wavelet Transform (DWT). A low pass filter and a high pass filter are chosen, such that they exactly halve the frequency range between themselves. This filter pair is called the Analysis Filter pair. First, the low pass filter is applied for each row of data, thereby getting the low frequency

components of the row. But since the lpf is a half band filter, the output data contains frequencies only in the first half of the original frequency range. So, by Shannon's Sampling Theorem, they can be subsampled by two, so that the output data now contains only half the original number of samples. Now, the high pass filter is applied for the same row of data, and similarly the high pass components are separated, and placed by the side of the low pass components. This procedure is done for all rows. Next, the filtering is done for each column of the intermediate data. The resulting two-dimensional array of coefficients contains four bands of data, each labeled as LL (low-low), HL (high-low), LH (low-high) and HH (high-high). The LL band can be decomposed once again in the same manner, thereby producing even more subbands. This can be done up to any level, thereby resulting in a pyramidal decomposition as shown in the figure.1 [7].

|   |   |
|---|---|
| LL | HL |
| LH | HH |

(a) Original Image          ( b) Single Level Decomposition

| LL | HL | HL |
| LH | HH | |
| LH | | HH |
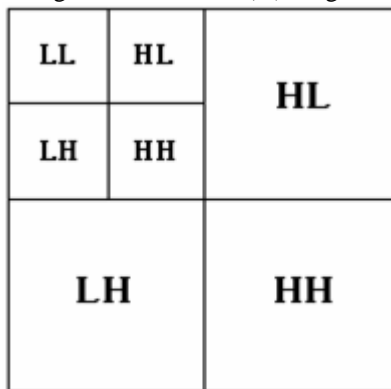
(c)  Two Level Decomposition
Fig.1 Pyramidal Decomposition

## Haar Wavelet Transform

The Haar transform is commonly applied tool used in the wavelet transform for the image decomposition and feature extraction. The

mathematical analysis of Haar transform is used for image compression and image pixels features extraction using decomposition and reconstruction matrices. Haar transform is the simplest compression process of this type.

The wavelet transform offers great design flexibility [5]. First must be explaining how wavelet transform works. Consider the following pixel matrix P representing 8x8 image :  P =

| 576 | 704 | 1152 | 1280 | 1344 | 1472 | 1536 | 1536 |
|-----|-----|------|------|------|------|------|------|
| 704 | 640 | 1156 | 1088 | 1344 | 1408 | 1536 | 1600 |
| 768 | 832 | 1216 | 1472 | 1472 | 1536 | 1600 | 1600 |
| 832 | 832 | 960  | 1344 | 1536 | 1536 | 1600 | 1536 |
| 832 | 832 | 960  | 1216 | 1536 | 1600 | 1536 | 1536 |
| 960 | 896 | 896  | 1088 | 1600 | 1600 | 1600 | 1536 |
| 768 | 768 | 832  | 832  | 1280 | 1472 | 1600 | 1600 |
| 448 | 768 | 704  | 640  | 1280 | 1408 | 1600 | 1600 |

To demonstrate how wavelet transform work, first describe transforming data string called averaging and differencing. Treat each row as separate data string for instance, the first row in the matrix P above consider the table below. Successive rows of the following table T show the starting, intermediate, and final results are:T=

| 576  | 704   | 1152 | 1280 | 1344 | 1472 | 1536 | 1536 |
|------|-------|------|------|------|------|------|------|
| 640  | 1216  | 1408 | 1536 | -64  | -64  | -64  | 0    |
| 928  | 1472  | -288 | -64  | -64  | -64  | -64  | 0    |
| 1200 | -272  | -288 | -64  | -64  | -64  | -64  | 0    |

Since the data string has length 2^3=8, there are three steps in transform process. The first four numbers in the second row are the averages of pairs in first row. Similarly, the first two numbers in the third row are the averages of those four averages taken two at a time and the first entry in the last row is the average of the preceding two computed averages. The remaining numbers, shown in bold, measure deviations from the various averages. The first from the first elements of the pairs that gave rise to them: subtracting 640, 1216, 140, 1536 from 576, 1152, 1344, 1536, element by element yields 64, 64, 64 and 0. These are called detail coefficients. They are repeated in each subsequent row of the table. The third and fourth entries in the third row are obtained by subtracting the first and second entries in that row from the first elements of the pairs that start row two subtracting 928, 1472 from 640,1408 element by element yields 288, 64.These two new detail coefficients are also repeated in each subsequent row of the table. Finally, the second entry in the last row, 272 is the detail coefficient obtained by subtracting the overall average 1200 from the 928 that starts row three. Averaging and differencing is a reversible process. Here we have lost nothing during transformation. After completing this process on all rows, we

move forward in doing the same transformation on columns. The final result is a new 8x8 matrix T, called the Haar wavelet transform of P. When applying the averaging and differencing technique to P, we will get the transformed matrix T as follows:T=

| 1212 | -306 | -146 | -54 | -24 | -68 | -40 | 4 |
|------|------|------|-----|-----|-----|-----|-----|
| 30 | 36 | -90 | -2 | 8 | -20 | 8 | -4 |
| -50 | -10 | -20 | -24 | 0 | 72 | -16 | -16 |
| 82 | 38 | -24 | 68 | 48 | -64 | 32 | 8 |
| 8 | 8 | -32 | 16 | -48 | -48 | -16 | 16 |
| 20 | 20 | 56 | -16 | -16 | 32 | -16 | -16 |
| -8 | 8 | -48 | 0 | -16 | -16 | -16 | -16 |
| 44 | 36 | 0 | 8 | 80 | -16 | -16 | 0 |

This matrix has one overall average value in the top left hand corner, and 63 detail elements The point of the wavelet transform is that regions of little variation in the original data manifest themselves as small or zero elements in the wavelet transformed version. The 0's in T are due to the occurrences of identical adjacent elements in P , and the - 2; -4, and 4 in T can be explained by some of the nearly identical adjacent elements in P . A matrix with a high proportion of zero entries is said to be sparse [8] & [9].
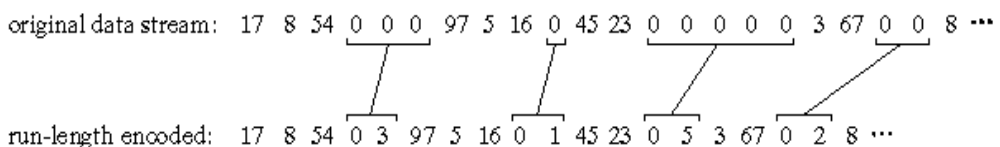
## Lossless Compression (Run length encoding)
If data have been losslessly compressed, the original data can be recovered exactly from the compressed data. It is generally used for applications that cannot allow any difference between the original and reconstructed data.

Run Length Encoding, sometimes called recurrence coding, is one of the simplest data compression algorithms. It is effective for data sets that are comprised of long sequences of a single repeated character. For instance, text files with large runs of spaces or tabs may compress well with this algorithm. Old versions of the arc compression program used this method. RLE finds runs of repeated characters in the input stream and replaces them with a three-byte code. The code consists of a flag character, a count byte, and the repeated characters. For instance, the string:

"AAAAAABBBBCCCCC" could be more efficiently represented as: "*A6*B4*C5". That saves us six bytes [10].

Run-length encoding can be used on only one of the characters (as with the zero below), several of the characters, or all of the characters.

original data stream:  17  8  54  0  0  0  97  5  16  0  45  23  0  0  0  0  0  3  67  0  0  8  ⋯

run-length encoded:  17  8  54  0  3  97  5  16  0  1  45  23  0  5  3  67  0  2  8  ⋯

Example of run-length encoding, each run of zeros is replaced by two characters in the compressed file: a zero to indicate that compression is occurring, followed by the number of zeros in the run [11].

**The proposed algorithm**

This research introduces an algorithm to image compression depend on wavelet transform. It combines two ways of image compression; lossy and lossless compression to reduce the redundancy of the image with a guarantee the quality of reconstructed image behind the transmission or storage. The following steps illustrate the proposed algorithm:

Input: Original image file (.bmp).

Output: Compressed image.

Process:

Step 1: Apply Haar wavelet transform on the image matrix and decompose it for two levels.

Step 2: The DWT algorithm is implemented by quantization the DWT coefficients. This is done by rounding the coefficients to the nearest integer. The aim of this process is to reduce the image data to perform the compression.

Step 3: Using a threshold that was selected and applied for wavelet transformed values. This technique is divided the input image into two sub-images. When the value is less than or equal to the threshold is set to zero, otherwise stay with the same value. This technique is considered the simplest method for image segmentation and it's used widely but the difficulty lies in finding appropriate value of the threshold that leads to accurate classification of image values.

Let I(i, j) represents the values of image after applying the threshold, where p( i, j ) refers to the value of the pixel in position (i,j) and T is the value of threshold.

$$I(i.j) = \begin{cases} p(i.j) & \mid p(i.j) \mid > T \\ 0 & \mid p(i.j) \mid \leq T \end{cases}$$

Step 4: Finally, Apply entropy coding which is a lossless compression by representing frequently occurring patterns with few bits and rarely occurring patterns with many bits. Run length coding is one of the most popular coders which was used and applied in our algorithm as mentioned previously above. Step 5: End.

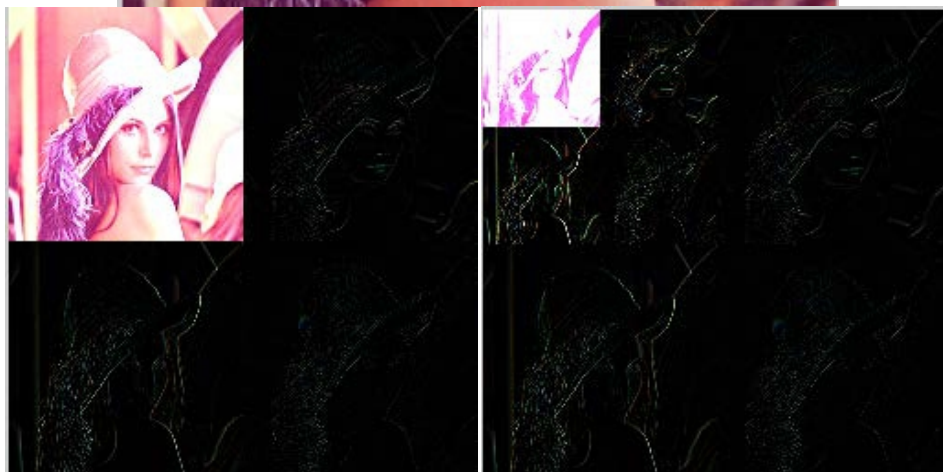Figure.2 & 3 illustrates two level decomposition applied for two images samples as below:
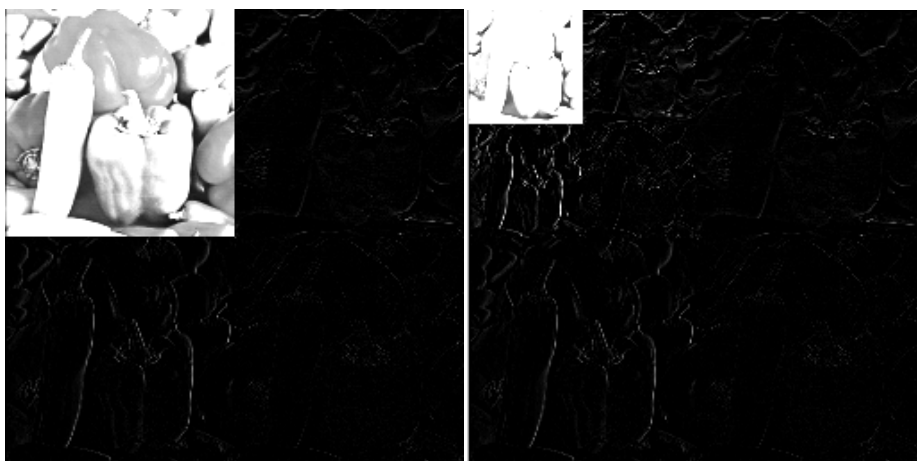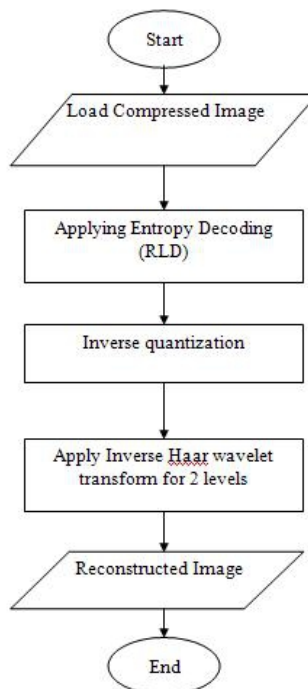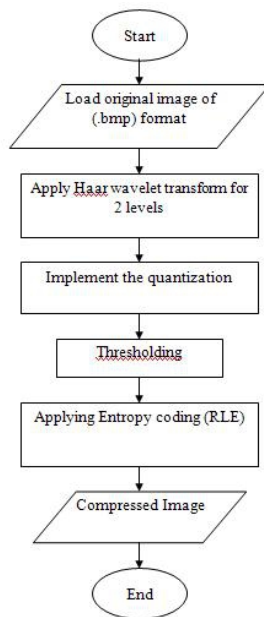
Fig.2 Lena Image under Two Level Decomposition

Fig.3 Pepper Image under Two Level Decomposition

Figure 4 show the block diagram of decomposition process while figure 5 shows the block diagram of the reconstruction process.

```
          ┌─────────┐
          │  Start  │
          └─────────┘
               │
        ╱─────────────────╲
       │ Load original image of │
       │   (.bmp) format   │
        ╲─────────────────╱
               │
      ┌──────────────────────┐
      │ Apply Haar wavelet transform for │
      │        2 levels       │
      └──────────────────────┘
               │
      ┌──────────────────────┐
      │ Implement the quantization │
      └──────────────────────┘
               │
        ┌──────────────┐
        │ Thresholding │
        └──────────────┘
               │
      ┌──────────────────────┐
      │ Applying Entropy coding (RLE) │
      └──────────────────────┘
               │
        ╱─────────────────╲
       │  Compressed Image  │
        ╲─────────────────╱
               │
          ┌─────────┐
          │   End   │
          └─────────┘
```

```
          ┌─────────┐
          │  Start  │
          └─────────┘
               │
        ╱─────────────────╲
       │ Load Compressed Image │
        ╲─────────────────╱
               │
      ┌──────────────────────┐
      │ Applying Entropy Decoding │
      │          (RLD)        │
      └──────────────────────┘
               │
      ┌──────────────────────┐
      │  Inverse quantization │
      └──────────────────────┘
               │
      ┌──────────────────────┐
      │ Apply Inverse Haar wavelet │
      │  transform for 2 levels │
      └──────────────────────┘
               │
        ╱─────────────────╲
       │ Reconstructed Image │
        ╲─────────────────╱
               │
          ┌─────────┐
          │   End   │
          └─────────┘
```

**Experimental Results**

In this paper, image compression algorithm depends on discrete wavelet transform and entropy coding is suggested. Two images (.bmp format) and (256×256) pixels are used as samples to test the algorithm. The peak signal-to-noise ratio (PSNR) which is one of the most popular measurements is used to estimate the quality of reconstructed images. Table.1 presents the experimental results of PSNR when applying the proposed algorithm on two samples of images with different values of threshold. When looking at the results in the table.1, we notice that PSNR gives better results when the thershold values is less than or equal to 20 while gets lower results in PSNR when threshold values are greater than the same value. Therefore, it can be getting a better quality of images throughout greater values of PSNR.

Table.1 The results of PSNR & CR for different threshold values

| Image Samples / Threshold Values | | Lena | Pepper |
|---|---|---|---|
| 10 | PSNR | 35.83 | 36.63 |
|    | CR | 5.21 | 5.04 |
| 20 | PSNR | 32.13 | 32.83 |
|    | CR | 7.69 | 7.64 |
| 30 | PSNR | 29.21 | 30.72 |
|    | CR | 10.96 | 9.44 |
| 40 | PSNR | 28.59 | 29.19 |
|    | CR | 11.22 | 10.90 |
| 50 | PSNR | 27.01 | 28.16 |
|    | CR | 12.47 | 11.89 |

On the other hand, because the inverse proportion relationship between PSNR and the compression ratios which gives opposite results under the same thresholds. So that, we must choose the threshold value of 20 to get high compression ratios and a better quality of image in the same time, which is considered a typical and justify the above mentioned restrictions for the two samples of images. Figures.6 & 7 show the original images and reconstructed images under the same selected threshold value.

(a ) Original image                        (b) Reconstructed image

Fig.6 Lena image



(a ) Original image                        (b) Reconstructed image

Fig.7 Pepper image

**Conclusion**

This research presents a developed image compression algorithm by combining lossy and lossless methods. The algorithm presents a technique provides high compression ratio with better quality of image. Two images of (.bmp) format as samples and different threshold values were used to test the performance of the proposed algorithm. From the observation to the experimental results of PSNR, it can be concluded that when testing the reconstructed image under different values of threshold, a threshold value of 20 showed good performance throughout giving high compression ratio with a better quality of image at the same time. Therefore, we can say the mentioned threshold value is a good choice and it can be adopted as a typical value of threshold.

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