

# Digital Image Processing and Compression: A Descriptive Study and Comparison of Fundamental Algorithms

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**Abstract :** Image compression is one of the advantageous techniques in different types of multi-media services. Image Compression technique have been emerged as one of the most important and successful applications in image analysis. The process of reducing the size of a data file is often referred to as data compression. In this paper the proposal of image compression using simple coding techniques called Huffman; Discrete Wavelet Transform (DWT) coding and fractal algorithm is deeply studied and compared. This paper is best recommended for new researchers studying digital image processing and various algorithms for further elaborations.

**Index Terms** - Error resilience, image coding, image compression, Huffman algorithm.

## I. INTRODUCTION

The process of reducing the size of a data file is often referred to as data compression. In the context of data transmission, it is called source coding; encoding done at the source of the data before it is stored or transmitted.[4] Source coding should not be confused with channel coding, for error detection and correction or line coding, the means for mapping data onto a signal.

Compression is useful because it reduces resources required to store and transmit data. Computational resources are consumed in the compression process and, usually, in the reversal of the process (decompression). Data compression is subject to a space–time complexity trade-off. For instance, a compression scheme for video may require expensive hardware for the video to be decompressed fast enough to be viewed as it is being decompressed, and the option to decompress the video in full before watching it may be inconvenient or require additional storage. The design of data compression schemes involves trade-offs among various factors, including the degree of compression, the amount of distortion introduced (when using lossy data compression), and the computational resources required to compress and decompress the data.

An image usually consists of enormous amount of data and requires large number of space in the memory. If more number of data is required for transmission then it takes much time to deliver the data to the receiver. Thus by using image compression techniques the time consumption can be greatly reduced. In this method, the elimination of redundant data in an image can be possible. Compressed image occupies less number of spaces in memory and it requires less time to transmit the information from transmitter to receiver. Compression means to make file size smaller by reorganizing the data in the file. Compressing imagery is different than zipping files. The main function of image compression is that it will rearrange the data and may degrade it to accomplish preferred compression level, depending on the compression ratio. If there is better compression ratio, the smaller the file size here more data is packed into smaller space, but lower the quality of the compressed product. A digital image which can be obtained by sampling and quantizing a continuous tone picture requires large number of storage area. For example, if we want to send an image with 512×512 pixels it will occupy 1GB storage on a particular disk and also if we want to add two or more images of same size in that same disk it will not be able to fit in a single disk. Thus, in order to transmit such an image over 32.8 Kbps modem would almost take 6-10 minutes. The main purpose for this image compression is to reduce the quantity of data that is essential for representing the sampled digital images and hence reduce the cost for storage space and communication. [1] Fig 1. General Block Diagram of Image Compression Figure 1 explains the block diagram of Image Compression. First we need transform the input Image using Forward Transform and again we quantizing the input Image using Quantization and then following the Entropy encoding and finally we are getting the Compressed Image. These are the steps followed in Compression Techniques. Here, the Image Compression Techniques is divided into two types namely Lossy and Lossless Techniques. In lossy, some amount of information in the given image is lost during compression of Image whereas in lossless compression no information in the given particular image is lost during Image Compression. Fractal algorithm comes under Lossy Compression. Discrete Wavelet Transform (DWT) and Huffman Coding comes under Lossless Image Compression.

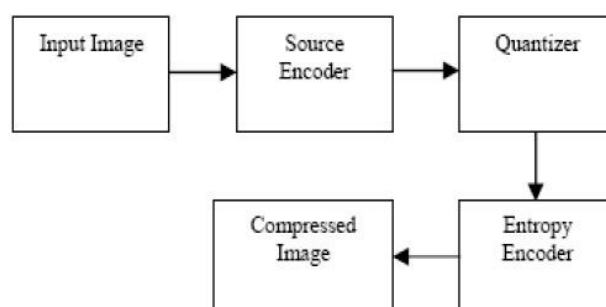


FIG: 1 block diagram of image compression.

## II. DIGITAL IMAGE COMPRESSION

The principle of digital image compression based on —information theory. Image compression uses the concept of ‘Entropy’ to measure the amount of information that a source produces. The amount of information produced by a source is defined as its entropy. For each symbol, there is a product of the symbol probability and its logarithm. The entropy is a negative summation of the products of all the symbols in a given symbol set.

Compression algorithms are methods that reduce the number of symbols used to represent source information, therefore reducing the amount of space needed to store the source information or the amount of time necessary to transmit it for a given channel capacity. The mapping from source symbols into fewer target symbols is referred to as ‘compression’. The transformation from the ‘target symbols’ back into the source symbols representing a close approximation form of the original information is called ‘decompression’. Compression system consist of two steps, sampling and quantization of a signal. The choice of compression algorithm involves several conflicting considerations. These include degree of compression required, and the speed of operation. Obviously if one is attempting to run programs direct from their compressed state, decompression speed is paramount. The other consideration is size of compressed file versus quality of decompressed image. Compression is also known as encoding process and decompression is known as decoding process [20]. Digital data compression algorithms can be classified into two categories-

### 1. Lossless compression

In lossless image compression algorithm, the original data can be recovered exactly from the compressed data. It is used generally for discrete data such as text, computer generated data, and certain kinds of image and video information. Lossless compression can achieve only a modest amount of compression of the data and hence it is not useful for sufficiently high compression ratios. GIF, Zip file format, and Tiff image format are popular examples of a lossless compression [18, 3]. Huffman Encoding and LZW are two examples of lossless compression algorithms. There are times when such methods of compression are unnecessarily exact.

In other words, ‘Lossless’ compression works by reducing the redundancy in the data. The decompressed data is an exact copy of the original, with no loss of data.

### 2. Lossy compression

Lossy compression techniques refer to the loss of information when data is compressed. As a result of this distortion, must higher compression ratios are possible as compared to the lossless compression in reconstruction of the image. ‘Lossy’ compression sacrifices exact reproduction of data for better compression. It both removes redundancy and creates an approximation of the original.

The JPEG standard is currently the most popular method of lossy compression. The degree of closeness is measured by distortion that can be defined by the amount of information lost. Some example of lossless compression techniques are : ‘CCITT T.6’, Zip file format, and Tiff image format. JPEG Baseline and JPEG 2000 is a example of lossy compression algorithm. The three main criteria in the design of a lossy image compression algorithm are desired bit rate or compression ratio, acceptable distortion, and restriction on coding and decoding time. While different algorithms produce different type of distortion, the acceptability of which is often application dependent, there is clearly an increase in distortion with decreasing bit rate.

Obviously, a lossy compression is really only suitable for graphics or sound data, where an exact reproduction is not necessary. Lossy compression techniques are more suitable for images, as much of the detail in an image can be discarded without greatly changing the appearance of the image. In practice, very fine details are lost in image compression.

## III. BASIC ALGORITHMS CURRENTLY BEING USED

- 1) **Huffman Coding:** Huffman coding is an entropy encoding algorithm used for lossless image compression. Huffman coding is efficient technique for image compression to some extent. [1] The last two decades has seen considerable improvements in image and video compression techniques. Variable length coding, such as Huffman code, is widely used to increase coding efficiency. It uses the Huffman source-coding algorithm to generate the uniquely decipherable Huffman code with a minimum expected codeword length when the probability distribution of a data source is known to the encoder. [2]

Entropy can be defined as a measure of information content; it will be able to represent the amount of bits used in the data in particular given image. Huffman coding uses a specific method for choosing the representation for particular images which results in a prefix code. The Compression of Images and data is both possible using Huffman Coding Algorithm. By using this Huffman algorithm we can be able to design the most efficient compression method. Huffman Coding comes under lossless technique here in lossless compression no information is lost during Image Compression.

- 2) **Fractal Algorithm** Fractal image compression comes under the type of lossy compression among the two types in Image Compression methods. The main idea in this algorithm is to divide the image into segments by using standard image processing techniques such as color partition, edging, and spectrum and quality analysis. Then each segment in the given image is looked up in a library of fractals. [6]

Image compression methods can also be divided as two different types namely, symmetrical and asymmetrical. Fractal image compression is the common example of asymmetrical methods. Image Compression using this Algorithm takes less execution time to compress the given 512×512 images than Huffman Coding. Fractal algorithm can be used to deal with both encoding and decoding methods and here Fractal encoding is mainly used to convert bitmap images to fractal codes. Two important benefits are immediately observed by converting conventional bitmap images to fractal data. The first is the ability to modify the division of fractal images. The second benefit is that there will be particular size of the data for each and every image and this size of data in a given input image will be used to store the fractal codes which are smaller than the size of original data in an image. Then the process of matching fractal is done with the fractal codes. This process will not look for exact matches, but it will look for ‘best fit’ matches based on the compression parameters. Fractal compression algorithm is entirely different from other lossy compression algorithms.

- 3) **Discrete Wavelet Transform(DWT)** DWT plays an important role to compress the given image without the loss of any information in that particular image. DWT comes under lossless type of image compression. Here, DWT can be mainly used in the transformation of a discrete time signal to Discrete Wavelet Representation. DWT usually based on time-

scale representation, which can be able to provide multi-resolution. Wavelets have more advantages over compressing signals. The wavelet transform is considered as the most advantageous and useful computational tools for a multiplicity of signal and image processing applications. Wavelet transforms are mainly used for images to reduce unwanted noise and blurring. [14] Wavelet transform has emerged as most powerful tool for both data and image compression. Wavelet transform performs multi resolution image analysis. The DWT has successfully been used in many image processing applications including noise reduction, edge detection, and compression. Indeed, the DWT is an efficient decomposition of signals into lower resolution and details. From the deterministic image processing point of view, DWT may be viewed as successive low-pass and high-pass filtering of the discrete time-domain signal. [13] In 2D image, the images are generally considered to be matrices with N rows and M columns. In wavelet transform, the decomposition of a particular image consists of two parts, one is lower frequency or approximation of an image (scaling function) and another is higher frequency or detailed part of an image (wavelet function). Figure 2 explains Wavelet Filter decomposition of an image where four different sub-images are obtained; the approximation (LL), the vertical detail (LH), the horizontal detail (HL) and the diagonal detail (HH). LL3 LH3 LH2 LH1 HL3 HH3 HL2 HH2 HL1 HH1 Fig 2. Wavelet Filter Decomposition

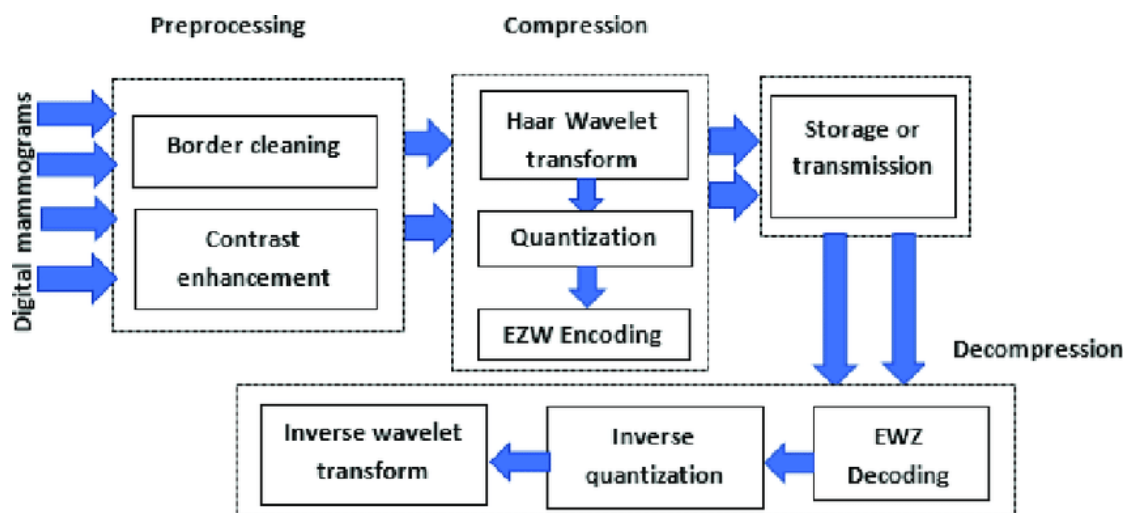


FIG 2: Block diagram of processing using wavelet technique.

#### IV. APPLICATIONS OF IMAGE PROCESSING

1. Intelligent Transportation Systems – This technique can be used in Automatic number plate recognition and Traffic sign recognition.
2. Remote Sensing – For this application, sensors capture the pictures of the earth's surface in remote sensing satellites or multi – spectral scanner which is mounted on an aircraft. These pictures are processed by transmitting it to the Earth station.
3. Moving object tracking – This application enables to measure motion parameters and acquire visual record of the moving object. The different types of approach to track an object are:
  - Motion based tracking
  - Recognition based tracking
4. Defense surveillance – Aerial surveillance methods are used to continuously keep an eye on the land and oceans. This application is also used to locate the types and formation of naval vessels of the ocean surface.
5. Biomedical Imaging techniques – For medical diagnosis, different types of imaging tools such as X- ray, Ultrasound, computer aided tomography (CT) etc are used. The diagrams of X- ray, MRI, and computer aided tomography (CT) are given below.

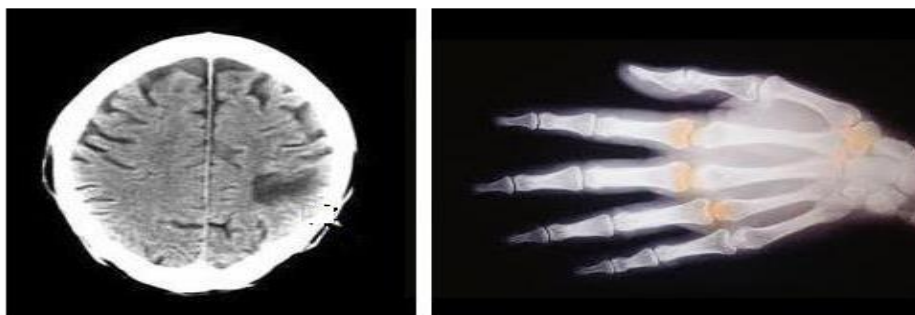


Fig. 3: Biomedical Images

Some of the applications of Biomedical imaging applications are as follows:

- *Heart ailment identity*– The critical diagnostic capabilities inclusive of length of the heart and its form are required to understand with a purpose to classify the coronary heart illnesses. To improve the analysis of heart sicknesses, photograph analysis strategies are employed to radiographic photos.
- *Lung disease identity* – In X- rays, the areas that appear darkish comprise air at the same time as area that appears lighter are solid tissues. Bones are extra radio opaque than tissues. The ribs, the coronary heart, thoracic backbone, and the diaphragm that separates the chest hollow space from the belly hollow space are clearly visible on the X-ray movie.

- Digital mammograms – This is used to discover the breast tumor. Mammograms can be analyzed using Image processing techniques including segmentation, form analysis, contrast enhancement, function extraction, etc.
- 6. Automatic Visual Inspection System – This software improves the quality and productivity of the product in the industries.
  - Automatic inspection of incandescent lamp filaments – This includes examination of the bulb manufacturing procedure.
  - Automatic surface inspection structures – In metallic industries it is important to come across the flaws at the surfaces.
  - Faulty factor identification – This software identifies the faulty components in digital or electromechanical structures.

A extensive research is being performed in the Image processing method. Different tools consisting of PET, MRI, and Computer aided Detection allows to diagnose and be privy to the tumor and other common ailment states. Development in photograph technology has formed the requirement to set up whether or not new technologies are effective and value useful. This era works underneath the subsequent regions:

Magnetic resonance imaging of the knee

Computer aided detection in mammography

Endoscopic ultrasound in staging the esophageal cancer

Magnetic resonance imaging in low again pain

Ophthalmic Imaging – This works under categories:

- i) Development of automated software- Analyzes the retinal images to show early sign of diabetic retinopathy
- ii) Development of instrumentation – Concentrates on development of scanning laser ophthalmoscope.

## V. Working of Fractal Algorithm

An image is the two dimensional (2-D) picture that gives appearance to a subject usually a physical object or a person. It is digitally represented by a rectangular matrix of dots arranged in rows and columns, or in other words, —An image may be defined as a two dimensional function  $f(x, y)$ , where  $x$  and  $y$  are spatial (plane) co-ordinates. The amplitude of  $f$  at any pair of co-ordinate  $(x, y)$  is called the intensity or gray level of the image at that point [3].

When  $(x, y)$  and amplitude values of  $f$  are all finite, discrete quantities, we call the image is a —DIGITAL IMAGE. A Digital image is an array of a number of picture elements called **pixels**. Each pixel is represented by a real number or a set of real numbers in limited number of bits. Based on the accuracy of the representation, we can classify image into three categories-

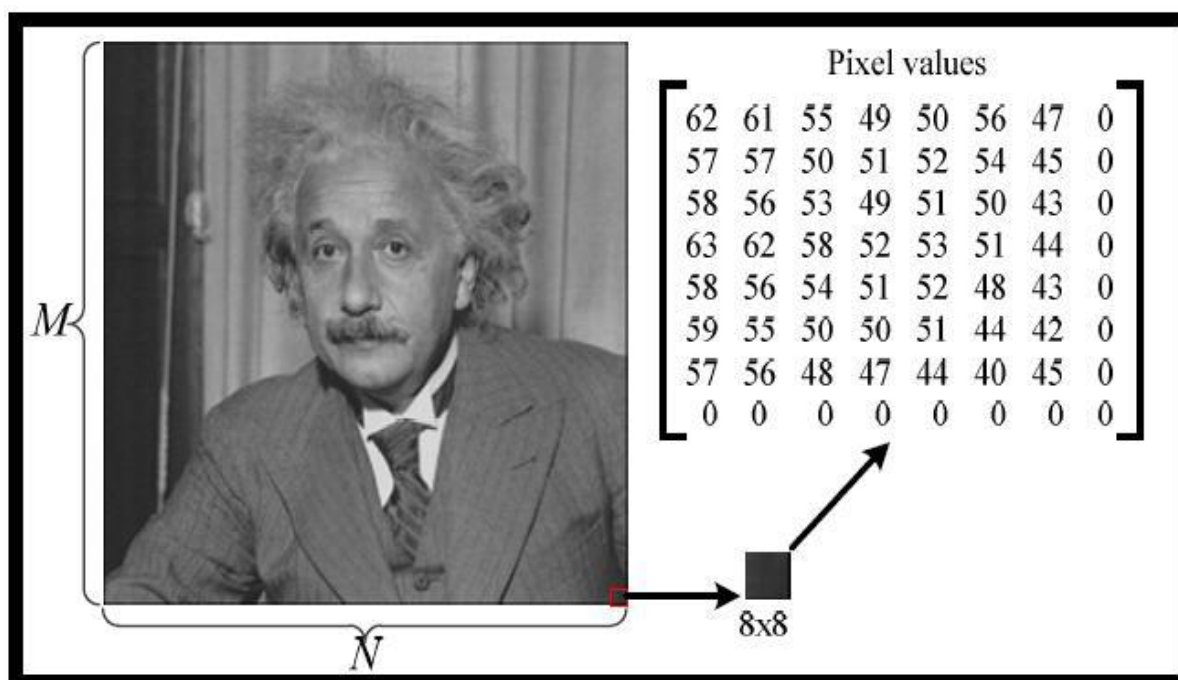
1. Black and White images
2. Grayscale images
3. Colour images

For Black and White images, each pixel is represented by one bit. These images are also called as **bi-level, binary, or bi-tonal** images. In Grayscale images, each pixel is represented by a luminance or say intensity level. For pictorial images, gray scale images are represented by 256 gray levels or 8 bits [20]. In **Bit planes**, grayscale images can be transformed into a sequence of binary images by breaking them up into their bit-planes. If we consider the grey value of each pixel of an 8-bit image as an 8-bit binary word, then the 0th bit plane consists of the last bit of each grey value. Since this bit has the least effect in terms of the magnitude of the value, it is called the **least significant bit**, and the plane consisting of those bits the least significant bit plane. Similarly the 7th bit plane consists of the first bit in each value. This bit has the greatest effect in terms of the magnitude of the value, so it is called the **most significant bit**, and the plane consisting of those bits the most significant bit plane. In color images each pixel can be represented by luminance and chrominance components. Color images can also be represented in an alternative system which is also known as different color space. Some examples of popular colour spaces are RGB, CIELAB, HSV, YIQ and YUV. Since human visual system (HVS) are less sensitive to colour images than to luminance or brightness, RGB space has the advantage of providing equal luminance to human vision. YIQ color spaces separate grayscale information from colour data. This enables the same signal to be used for black and white settings. YIQ component are luminance(Y), hue (I) and saturation (Q). Grayscale information is expressed as luminance (Y), and colour information as chrominance, which is both hue (I) and saturation (Q). YCbCr is another colour space that has widely been used for digital video. Here, luminance information is stored as a single component (Y), and chrominance information is stored as two colour-difference components (Cb) and (Cr). Cb represents the difference between the blue component and a reference value, whereas Cr represents the difference between the red component and a reference value. Another type of colour space is CMYK which is used in colour printers. The primaries in this colour space are cyan (C), magenta (M), yellow (Y) and black (K). Resolution in an image refers to the capability to represent the finer details [2]. The RGB color space is a linear, additive, device-dependent color space. Each value is usually represented as unsigned integers in the range from 0 to 255, giving a total color depth of  $3 \times 8 = 24$  bits[12].



Colour	Red	Blue	Green
Black	0	0	0
White	255	255	255
Yellow	255	255	0
Dark Green	0	100	0

MPEG standard use luminance **Y** and two chrominance **CB** and **CR** to represent color. Figure 2.1 shows the standard image 'Einstein'. The size of the row (**M**) and column (**N**) gives the size (or resolution) of **M X N** image. A small block (8 X 8) of the image is indicated at the lower right corner in the form of matrix. Each element in the matrix represents the dots of the image. Each dot represents the pixel value at that position .



Intensity **I** in RGB model is calculated by

$$I = 0.3R + 0.59G + 0.11B \quad (2.1)$$

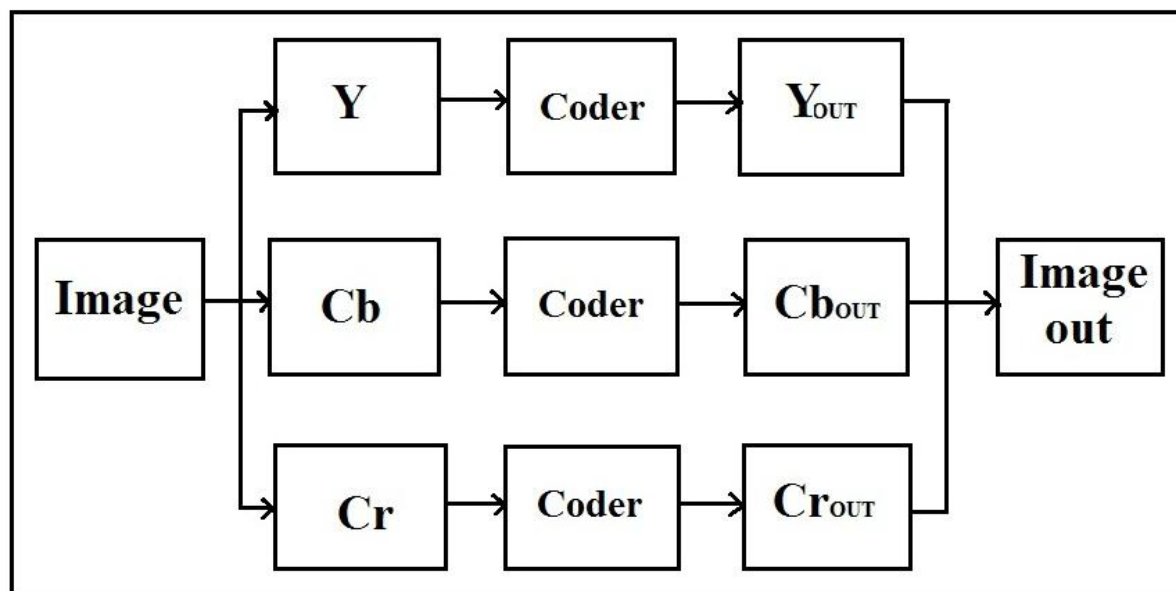
This is the same method used for calculating the **Y** value when converting from RGB to YCBCR. RGB images are converted into more suitable YCBCR color format using the following equations.

$$Y = 0.299 R + 0.587 G + 0.114 B \quad (2.2)$$

$$CB = -0.169 R - 0.331 G + 0.500 B = 0.564 (B - Y) \quad (2.3)$$

$$CR = 0.500 R - 0.419 G - 0.081 B = 0.713 (R - Y) \quad (2.4)$$

Where **Y** represents a monochrome compatible luminance component, and **CB**, **CR** represent chrominance components containing color information. Most of image/video coding standards adopt YCBCR color format as an input image signal . Figure shows a block diagram of the color space conversion. Each of the three components (**Y**, **Cb**, and **Cr**) is input to the coder. The PSNR is measured for each compressed component (**Yout**, **Cbout**, and **Crout**) just as we do for gray scale images.



The three output components are reassembled to form a reconstructed 24-bit color image



## VI. Redundancy

Redundancy different amount of data might be used. If the same information can be represented using different amounts of data, and the representations that require more data than actual information, is referred as data redundancy. In other words, Number of bits required to represent the information in an image can be minimized by removing the redundancy present in it [41]. Data redundancy is of central issue in digital image compression. If  $n_1$  and  $n_2$  denote the number of information carrying units in original and compressed image respectively, then the compression ratio CR can be defined as  $CR = n_1/n_2$ ; (2.5)

And relative data redundancy RD of the original image can be defined as

$$RD=1-1/CR \quad (2.6)$$

Three possibilities arise here:

- (1) If  $n_1=n_2$ , then  $CR=1$  and hence  $RD=0$  which implies that original image do not contain any redundancy between the pixels.
- (2) If  $n_1 \gg n_2$ , then  $CR \rightarrow \infty$  and hence  $RD > 1$  which implies considerable amount of redundancy in the original image.
- (3) If  $n_1 \ll n_2$ , then  $CR < 0$  and hence  $RD \rightarrow -\infty$  which indicates that the compressed image contains more data than original image.

There are three kinds of redundancies that may present in the image and video.

- I. Coding redundancy
- II. Interpixel redundancy
- III. Psychovisual redundancy

#### a) Coding redundancy

If the gray levels of an image are coded in a way that uses more code symbol than absolutely necessary to represent each gray level, the resulting image is said to be code redundancy.

In coding redundancy we assign equal number of bits for symbols of high probability and less probability. It is better to assign fewer bits for more probable gray level and assign more bits for less probable gray level, which will provide image compression. This method is called as —variable length coding. Coding redundancy would not provide the correlation between the pixels [17].

#### b) Interpixel redundancy

In most of the images because of the value of any given pixel can be reasonably predicted from the value of its neighbors, the information carried by individual pixel is relatively small. That's why we call this type of redundancy as a interpixel redundancy. In order to reduce the interpixel redundancy in an image is that to code the difference between the successive pixels and send it to the decoder side. This type of transformation is generally reversible and called —mapping.

#### c) Psychovisual redundancy

Certain information's has less relative importance than other information in normal visual processing. This information is said to be psychovisually redundancy. Its elimination is possible only because the information itself is not essential for normal visual processing.

The elimination of psychovisual redundant data results in a loss of quantitative information. It is commonly referred to as —quantization.

## VII. Coding

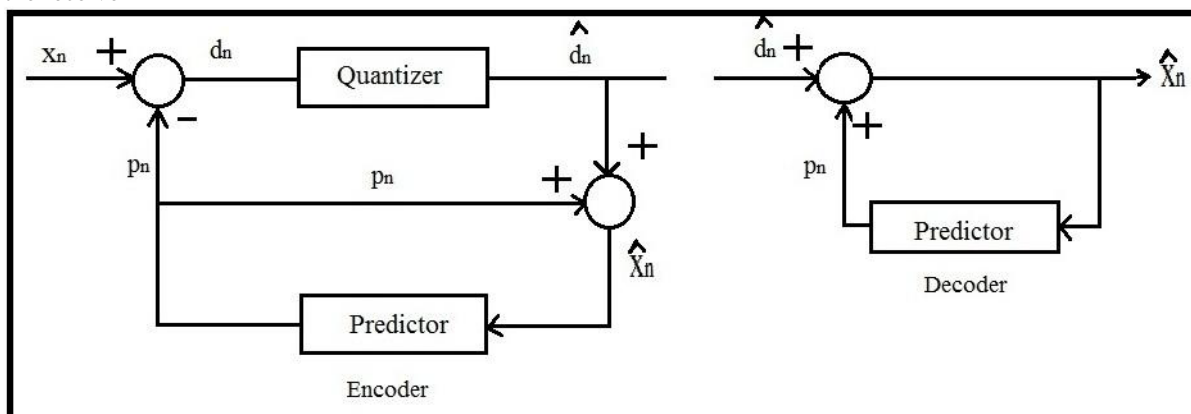
Various coding techniques are used to facilitate compression. Here are pixel coding, predictive coding and transform coding will be discussed [10]:

#### a) Pixel coding

In this type of coding, each pixel in the image is coded separately. The pixel values that occurs most frequently are assigned shorter code words (i.e. fewer bits), and those pixel values that are more rare (i.e. less probable) are assigned longer codes. That makes the average code word length decrease.

#### b) Predictive coding

As images are highly correlated from sample to sample, predictive coding technique is relatively simple to implement [20]. Predictive coding predicts the present values of the sample based on the past values and only encodes and transmits the difference between the predicted and the sample value. Differential pulse code modulation (DPCM) is an example of a frequently used predictive coding. The function of the predictor is to obtain an estimate of the current sample based on the reconstructed values of the past sample. The difference between this estimate, or prediction, and the actual value is quantized, encoded, and transmitted to the receiver



The decoder generates an estimate identical to the encoder, which is then added on to generate the reconstructed value. The requirement that the prediction algorithm use only the reconstructed values is to ensure that the prediction at both the encoder and the decoder are identical. The reconstructed values used by the predictor, and the prediction algorithm, are dependent on the nature of the data being encoded.

### c) Transform coding

In transform coding, an image is transformed from one domain (usually spatial or temporal) to a different type of representation, using some well-known transform. Then the transformed values are coded and thus provide greater data compression. In this thesis, transforms are orthogonal so that the mapping is unique and reversible. As a result, the energy is preserved in the transform domain that is the sum of the squares of the transformed sequence is the same as the sum of the squares of the original sequence. Thus, the image can be completely recovered by the inverse transform.

Transform coding (TC), is an efficient coding scheme based on utilization of interpixel correlation. Transform coding uses frequency domain, in which the encoding system initially converting the pixels in space domain into frequency domain via transformation function. Thus producing a set of spectral coefficients, which are then suitably coded and transmitted [14].

The transform operation itself does not achieve any compression. It aims at decorrelating the original data and compacting a large fraction of the signal energy into a relatively small set of transform coefficients (energy packing property). In this way, many coefficients can be discarded after quantization and prior to encoding. Most practical transform coding systems are based on DCT of types II which provides good compromise between energy packing ability and computational complexity. The energy packing property of DCT is superior to that of any other unitary transform [5]. Transforms that redistribute or pack the most information into the fewest coefficients provide the best sub-image approximations and, consequently, the smallest reconstruction errors. In Transform coding, the main idea is that if the transformed version of a signal is less correlated compared with the original signal, then quantizing and encoding the transformed signal may lead to data compression. At the receiver, the encoded data are decoded and transformed back to reconstruct the signal.

The purpose of the transform is to remove interpixel redundancy (or de-correlate) from the original image representation. The image data is transformed to a new representation where average values of transformed data are smaller than the original form. This way the compression is achieved. The higher the correlation among the image pixels, the better is the compression ratio achieved. There are various methods of transformations being used for data compression as follows :

- i. Karhunen-Loeve Transform (KLT)
- ii. Discrete Fourier Transform (DFT)
- iii. Discrete Sine Transform (DST)
- iv. Walsh Hadamard Transform (WHT)
- v. Discrete Cosine Transform (DCT)
- vi. Discrete Wavelet Transform (DWT)

Wavelets are a mathematical tool for changing the coordinate system in which we represent the signal to another domain that is best suited for compression. Wavelet based coding is more robust under transmission and decoding errors. Due to their inherent multiresolution nature, they are suitable for applications where scalability and tolerable degradation are important .

Wavelets are tool for decomposing signals such as images, into a hierarchy of increasing resolutions. The more resolution layers, the more detailed features of the image are shown. They are localized waves that drop to zero. They come from iteration of filters together with rescaling. Wavelet produces a natural multi resolution of every image, including the all-important edges. The output from the low pass channel is useful compression. Wavelet has an unconditional basis as a result the size of the wavelet coefficients drop off rapidly. The wavelet expansion coefficients represent a local component thereby making it easier to interpret. Wavelets are adjustable and hence can be designed to suit the individual applications. Its generation and calculation of DWT is well suited to the digital computer . They are only multiplications and additions in the calculations of wavelets, which are basic to a digital computer.

### d) Fractal Image Compression

Fractal coding is a new method of image compression. The main principle of the fractal transform coding is based on the hypothesis that the image redundancies can be efficiently exploited by means of block self-affine transformations. By removing the redundancy related to self-similarity in an image. Fractal image compression can achieve a higher compression ratio with high decoding quality. Fractal coding has the advantage such as resolution independence and fast decoding as compare to other image compression methods. So fractal image compression is a promising technique that has great potential to improve the efficiency of image storage and image transmission .

### e) Baseline Fractal Coding

Fractal image coding is based on partition iterated function system (PIFS), in which an original input image is partitioned into a set of non-overlapping sub-blocks, called range block (R) that cover up the whole image. The size of every range block is  $N \times N$ . At the same time, the original image is also partitioned into a set of other overlapping sub-blocks, called domain blocks (D), which size is always twice the size of range blocks. The domain blocks are allowed to be overlapping and need not cover the whole image . Secondly, each of the domain blocks is contracted by pixel averaging or down sampling to match the size of the range block. Next, eight symmetrical transformations (rotations and flips) are applied to all contracted domain blocks to bring out an extended domain pool, which denoted as  $\hat{D}$ . For each range block, we search the domain pool to get the best matched domain block  $D$  with a contractive affine transformation. The problem with fractal coding is the highly computational complexity in the encoding process



Most of the encoding time is spent on the best matching search between range blocks and numerous domain blocks ( ) so that the fractal encoding is a time consuming process, which limits the algorithm to practical application greatly. In order to solve this problem, lots of researches were done earlier to speed up the block matching process. Most of these improvements tried to restrict the search space of the domain block pool in order to reduce the computation requirements of the best matching search, hence speeding up the fractal image encoding procession

### VIII. Advantages and Disadvantages

Fractal image compression has the following advantages:

- Fast decoding process
- High compression ratio
- Low performance device
- Resolution independence
- It can be digitally scaled to any resolution when decoded.
- Image compressed in terms of self-similarity rather than pixel resolution
- Lower transmission time

Disadvantage of fractal image compression

- Long encoding time
- Image quality

### REFERENCES

1. Jagadish H. Pujar and Lohit M. Kadlaskar “A New Lossless Method Of Image Compression And Decompression Using Huffman Coding Techniques” Journal of Theoretical and Applied Information Technology , 2010.
2. Jian-Jiun Ding, Hsin-Hui Chen, and Wei-Yi Wei “Adaptive Golomb Code for Joint Geometrically” IEEE Transactions On Circuits And Systems For Video Technology, Vol. 23, No. 4, April 2013
3. Pawel Turcza and Mariusz Duplaga “Hardware-Efficient Low-Power Image Processing System for Wireless Capsule Endoscopy” IEEE Journal Of Biomedical And Health Informatics, Vol. 17, No. 6, November 2013.
4. I. Daubechies, —Ten Lectures on Wavelets, SIAM, 1992.
5. E. Whittaker, —On the Functions which are Represented by the Expansions of Interpolation Theory, Proc. Royal Soc., Edinburgh, Section A 35, pp. 181-194, 1915.
6. P. Vaidyanathan, —Multirate Systems and Filter Banks, Prentice-Hall, 1993.
7. D. LeGall and A. Tabatabai, —Subband Coding of Digital Images Using Symmetric Short Kernel Filters and Arithmetic Coding Techniques, Proc. ICASSP, IEEE, pp. 761-765, 1988.
8. D. Huffman, —A Method for the Construction of Minimum Redundancy Codes, Proc. IRE, pp. 1098-1101, 1952.
9. S. Mallat and F. Falzon, —Understanding Image Transform Codes, IEEE Trans. Im. Proc., submitted, 1997.
10. A. Oppenheim and R. Schaffer, —Discrete-Time Signal Processing, Prentice-Hall, 1989
11. Mark J. T. Smith and Steven L. Eddins. —Analysis/synthesis techniques for subband image coding, IEEE Trans. Acoust., Speech, Signal Process., pp. 1446–1456, August 1990
12. M. Antonini et al, —Image Coding Using Wavelet Transform, IEEE Trans. Image Proc., pp. 205-220, April, 1992
13. A. Gersho and R. Gray, —Vector Quantization and Signal Compression, Kluwer, 1992.
14. A. Lewis and G. Knowles, —Image Compression Using the 2-D Wavelet Transform, IEEE Trans. Image Proc., pp. 244-250, April. 1992.
15. J. Villasenor et al, —Wavelet Filter Evaluation for Image Compression, IEEE Trans. Image Proc., August, 1995.
16. S. Mallat, —A theory for multiresolution signal decomposition: The wavelet representation, IEEE Trans. Pattern Anal. Machine Intell. vol. 11 pp. 674-693, July 1989 the ACM, vol. 34, pp. 30-44, April 1991.
17. J. W. Woods ed. —Subband Image Coding, Kluwer Academic Publishers, Boston, MA. 1991.
18. A. Lewis and G. Knowles, —Image compression using the 2-D wavelet transforms,