Analysis of Different Image Compression Techniques: A Review

Garima Garg[a]*, Raman Kumar[b]

[a]Department of Computer Science and Engineering, IKGPTU, Kapurthala, Punjab, India, garimagarghce@gmail.com
[b]Department of Computer Science and Engineering, IKGPTU, Kapurthala, Punjab, India, er.ramankumar@aol.in

Abstract: The availability of images in a wide variety of applications has expanded due to technological developments that have not to influence the variety of image operations, the availability of advanced image modification software, or image management. Despite technological breakthroughs in storage and transmission, demand for storage capacity and communication bandwidth exceeds available capacity. As a result, image compression has proven to be a helpful technique. When it comes to image compression, we don't just focus on lowering size; we also focus without sacrificing image quality or information. The survey outlines the primary image compression algorithms, both lossy and lossless, and their benefits, drawbacks, and research opportunities. This examination of several compression techniques aids in the identification of advantageous qualities and the selection of the proper compression method. We suggested some general criteria for choosing the optimum compression algorithm for an image based on the review.

Keywords: Image Compression, types of images, performance assessment metrics, compression techniques.

1. Introduction

An image is a two-dimensional communication processed by the human visual system. The impulses that depict images are usually analog. Computer applications convert them from analog to digital for processing, storage, and transmission [1]. A digital image is a 2D pixel array. Image compression reduces the amount of storage space required for photos and movies, hence improving storage and transmission performance. Lossy or lossless image compression is possible. Lossless compression entails compressing data so that it may be decompressed into an identical reproduction of the original [2-4]. However, in lossy compression techniques, some of the image's finer details can be sacrificed in order to save a little more bandwidth or storage space.

Working procedure of image compression techniques:

The most common processes in compressing an image are [2]:

- Specifying the Rate (available bits) and Distortion (tolerable error) parameters for the target image.
- Classifying the visual data according to their relevance.
- Distributing the available bit budget across these classes in such a way that distortion is minimized.
- Using the bit allocation information acquired in step 3, quantify each class independently.
- Using an entropy coder, encode each class independently and save to a file. It is frequently faster to reconstruct an image from compressed data than it is to compress it. The procedures are as follows:
- Using the entropy decoder, read the quantized data from the file. (Step 5 is reversed.)
- Reduce the number of variables in the data. (Step 4 is reversed.)
- Re-create the image. (Step 2 is reversed.)

The following sections comprise this paper: section II explains the related work of researchers, section III defines the types of the different image compression techniques, and section IV concludes the paper by summarizing the conclusion.

2. Literature Review

Gharavi and Tabatabai (1988) proposed utilizing QMF to encode digital images. Using a 2-D separable QMF bank, the input signal spectrum is decomposed into numerous narrowband images [5]. To reduce redundant bits in data or images, Patel et al. (2016) introduced the Huffman coding technique, which analyses multiple features or specifications such as "Peak Signal to Noise Ratio (PSNR), Mean Square Error (MSE), Bits Per Pixel (BPP), and Compression Ratio (CR)" [6]. Kekre et al. (2016) proposed vector quantization for image compression. VQ is a multi-dimensional version of Scalar Quantization [7].

Zhang et al. (2020) proposed a multi-scale progressive statistical model-based lossless image compression system. The suggested statistical model effectively balances pixel-wise model accuracy and multi-scale model speed [8]. Mohammed and Abou-Chadi (2011) investigated picture compression techniques based on block truncation coding. For comparison purposes, the original block truncation coding (BTC) and the Absolute Moment block truncation coding (AMBTC) were used [9]. BTC breaks the original image into $n \times n$ sub-blocks, reducing the number of grey levels within each block. Sarkar et al. (2018) proposed a hybrid lossy image compression model using run-length encoding and Huffman coding by taking an example of two images i.e., clock.tiff and man.tiff. The other parameters like PSNR, MSE, and structural similarity remain almost the same while the storage size is reduced [10]. Table 1 summarizes the numerous image compression approaches that researchers in the past have used.

Table 1: Detailed Summary of various image compression techniques used by researchers

Author Name	Year	Title of Paper	Compression Technique used	Reference
Gharavi and Tabatabai	1988	"Sub-band coding of monochrome and color images"	Sub-band Coding (SBC)	[5]
Patel et al.	2016	"A fast and improved Image Compression technique using Huffman coding"	Huffman Encoding	[6]
Kekre et al.	2016	"Color image compression using vector quantization and hybrid wavelet transform"	Vector Quantization (VQ)	[7]
Zhang et al.	2020	"Lossless image compression using a multi-scale progressive statistical model"	Statistical Coding	[8]
Mohammed and Abou-Chadi	2011	"Image compression using block truncation coding	Block Truncation Coding (BTC)	[9]
Sarkar et al.	2018	"Novel Hybrid Lossy Image Compression Model using Run-Length Coding and Huffman Coding"	Run Length Encoding (RLE)	[10]

Li et al.	2018	"Efficient trimmed convolutional arithmetic encoding for lossless image compression"	Arithmetic Encoding	[11]
DeVore et al.	1992	"Image compression through wavelet transform coding"	Transform Coding	[12]
Cooper and Lorenc	2006	"Image compression using singular value decomposition"	Singular Value Decomposition (SVD)	[13]
Telagarapu et al.	2011	"Image compression using DCT and wavelet transformations"	Discrete Cosine Transform (DCT)	[14]
Leon-Salas et al.	2007	"A CMOS imager with focal plane compression using predictive coding"	Predictive Coding	[15]
Chowdhury and Khatun	2012	"Image compression using discrete wavelet transform"	Discrete Wavelet Transform (DWT)	[16]
Sun et al.	2008	"Image compression based on classification row by row and LZW encoding"	LZW Encoding	[17]
Liu et al.	2016	"A fractal image encoding method based on statistical loss used in agricultural image compression"	Fractal Compression	[18]

A 3D binary cuboid was encoded using a trimmed convolutional network (i.e., TCAE) by Li et al. (2018). To represent a vast context while keeping high computational efficiency, the fully convolutional network design may benefit from reduced convolution and execute probability prediction to all bits in a single forward pass [11]. DeVore et al. (1992) explained the concept of image compression through transform coding technique with the help of mathematical expressions in detail [12]. Cooper and Lorenc (2006) focused on image compression through Singular Value Decomposition (SVD). It is a valuable device for reducing data storage and transport. SVD is a matrix factorization that allows you to extract algebraic and geometric information from an image in a new way. Many fields have adopted SVD, including data compression, signal processing, and pattern analysis [13]. On the other hand, Telagarapu et al. (2011) compressed the three images by applying Discrete Cosine Transform (DCT). DCT represents the input data as a sum of cosine functions with variable frequencies and magnitudes. The most widely used DCTs are one-dimensional and two-dimensional [14].

To solve the problem of focal plane compression, Leon-Salas et al. (2007) developed a single-chip approach. In this study, a predictive coding technique was applied in the analog domain, followed by a compact entropy coder on-chip. Because of its lossless compression capability and ease of use, predictive coding was chosen [15]. Chowdhury and Khatun (2012) introduced the Discrete Wavelet Transform as a new approach (DWT). DWT is a multi-resolution image compression transform. This method uses sub-band coding to describe the signal's time-frequency [16]. Sun et al. (2008) suggested a near-lossless image compression algorithm that combined categorization, information hiding, and LZW. Similar pixels were obtained in the same sequence using classification and decomposition. To reduce data storage, the mask image was then concealed in these sequences. LZW was then used to encode the sequences. The algorithm was simple and had a higher compression ratio than previous approaches like LZW [17]. Fractal image compression was defined by Liu et al. (2016). The fractal compression technique works by comparing sections of an image to other parts of a similar image. Fractal algorithms decode images by converting geometric forms into mathematical data known as "fractal codes" [18].

3. Image Compression Techniques:

There are two types of image compression techniques: lossless and lossy compression. Decompression of lossless data results in an image that is identical to the original. These processes obliterate data, resulting in an image that is not identical to the original.

3.1 Lossless Compression:

The reconstructed image in lossless compression techniques is quantitatively identical to the original image. Only a limited amount of compression may be achieved with lossless compression. Lossless compression can cut the size of a file in half depending on the type of data being compressed. As a result, lossless compression is advantageous for delivering files over the Internet, as smaller files move more quickly. Generally, techniques for lossless image compression treat images as a collection of pixels ordered in row-major order. Each pixel is processed using two different procedures. The first step establishes a prediction for the next pixel's numeric value. This is often combined with an edge detection technique that attempts to account for intensity discontinuities. The difference between the anticipated and actual pixel values in the second phase is coded using an entropy coder and a probability distribution. Figure 1 shows the block diagram of the lossless compression technique. There are various types of lossless compression techniques, which are described in detail one by one.

3.1.1 Run Length Encoding

An alternative to lossy compression, RLE utilises a pair of (length, value) values to replace the original data. The value is unique and the length reflects the number of times it is repeated. This basic data compression technique uses runs to store compressed data in smaller chunks for easier retrieval later. Runs are patterns in which the same data value appears in multiple data items in a row. Rather of saving the original run, these sequences are preserved as a single data value and count. Consider the following illustration: a screen with solid white writing on a basic black background In the unoccupied zone, there will be many long lines of white pixels and many short runs of black pixels.

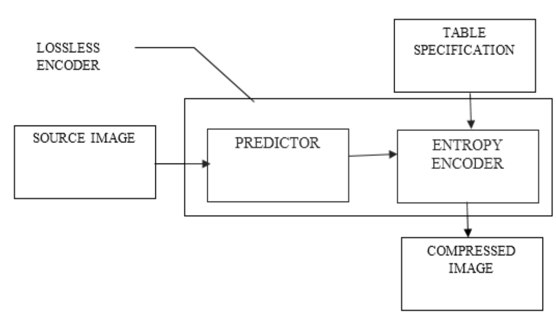

Fig. 1: Block Diagram for Lossless Compression

3.1.2 Statistical Coding

The statistical coding technique incorporates the following techniques such as Huffman Encoding, .Arithmetic Encoding, and LZW Encoding [8].

(i) Huffman Encoding

In Huffman coding, a data item's frequency is used (pixel in images). The goal is to encode data more frequently with fewer bits. The codes are kept in a Code Book for each image or collection of images. To enable decoding, the codebook and encoded data must be transmitted in all circumstances [6]. To encrypt images, follow these steps: First, divide the image up into 8 x 8 blocks, then each block is a symbol to be coded at the second step. Compute the Huffman codes for a set of the block at the next step and finally encode the blocks accordingly at the last step.

(ii) Arithmetic Coding

Rather than coding each symbol separately, this approach codes the entire visual sequence with a single code. As a result, nearby pixels' association is utilized. The following principle governs arithmetic coding [11]. The symbol alphabet is finite, as are all potential symbol sequences of a given length; all conceivable sequences are countable infinite; and we may assign a unique subinterval to each given input since the range [0,1] includes an unlimited number of real values (sequence of symbols).

(iii) LZW Coding

The LZW algorithm [17] is based on the number of character sequences in the encoded string. Its theory is to gradually develop a dictionary by substituting patterns with an index code. The ASCII table's 256 values are used to populate the dictionary. For monochromatic images (coded in 1 bit), each string is compared to the dictionary and added if it is not found. That is, if a string is never shorter than the dictionary's greatest word, it is conveyed. The algorithm rebuilds the dictionary while decoding; thus it doesn't need to be stored.

3.1.3 Predictive Coding

Another example of inter-pixel redundancy research is the Predictive Coding Technique [15], which uses the basic notion of encoding only new information in each pixel. The difference between the pixel's actual and intended value is frequently utilised to define this additional information. The prediction error is computed by rounding the predictor's output to the nearest integer and comparing it to the actual pixel value. Variable Length Coding can be used to encode this error (VLC). The paradigm utilized to describe the visuals is the method's distinguishing feature. The images are represented as non-causal random fields, in which the intensity of each pixel is determined by the intensities of sites in all directions around it.

3.2 Lossy Compression:

Figure 2 shows how a lossy compression system may analyze colour data for a range of pixels and detect subtle variances in pixel colour values that the human eye/brain couldn't distinguish differently. The computer may replace the others with smaller pixels whose color value disparities are within human vision. The pixels that have been finely graded are subsequently discarded. This type of compression can result in large file size savings, but the complexity of the algorithm dictates the image superiority of the final product.

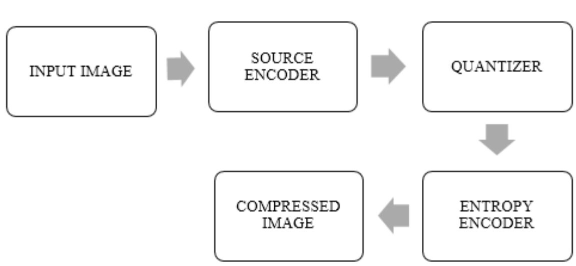

Fig. 2: Block Diagram for Lossy Compression

3.2.1. Transform Coding

Frequently, the original picture is divided into smaller sub-images (blocks) (usually 8 x 8). It transforms the eight pixel values into an array of coefficients closer to the top-left corner, which typically includes the bulk of the information required to quantify and encode a picture with little perceptual distortion. The quantized coefficients are then utilized for encoding the image's bitstream. The decoder uses the same process, except that the 'dequantization' stage only approximates the real coefficient values. In other words, the quantizer's loss in the encoder step is irreversible.

3.2.2. Block Truncation Coding

BTC is a grayscale picture compression technique [9]. It employs a quantizer to decrease the number of grey levels inside each block while maintaining the mean and standard deviation. Although BTC compression was used to compress color long before DXTC, it is an early ancestor of the popular hardware DirectX Texture Compression (DXTC) technology. If 8-bit integer values are employed during transmission or storage, sub-blocks of 4 × 4 pixels allow for around 25% compression. Larger blocks allow for more compression, but due to the method's nature, quality suffers as block size grows.

3.2.3. Sub-band Coding

It divides the signal's frequency range into sub-bands and then codes each sub-band with a coder and bit rate that fit the band's statistics [5]. This is because SBC allows for variable bit assignment between sub-bands and coding error confinement within sub-bands. The decoded sub-band signals are un-sampled and routed through a bank of synthesis filters before being appropriately summed at the decoder.

3.2.4. Vector Quantization

Vector quantization (VQ) techniques apply scalar quantization ideas to several dimensions. This method entails creating a code vector dictionary, which is a collection of fixed-size vectors. After that, the image is separated into image vectors, or non-overlapping pieces [7]. The dictionary's closest match vector is then discovered for each picture vector, and its index in the dictionary is used as the original image vector's encoding. VQ-based coding schemes are particularly well-suited for multimedia applications due to their decoder-side search capabilities.

3.2.5. Fractal Compression

The fractal compression technique works by comparing regions of photos to other images. Algorithms convert these pieces, or geometric shapes, into "fractal codes" that may be used to replicate the encoded image. When converted to fractal coding, an image loses its resolution-dependent relationship. The image can be reconstructed to fit any screen size without pixel-based compression artifacts or loss of quality [18].

3.2.6. Singular Value Decomposition (SVD)

Linear algebra is used extensively in data compression. In today's society, the necessity to reduce the amount of digital data saved and communicated is becoming increasingly important. Singular Value Decomposition [16] is a valuable technique for minimizing data storage and transport. SVD is a matrix factorization that allows you to extract algebraic and geometric information from an image in a new way. Many fields have adopted SVD, including data compression, signal processing, and pattern analysis [4]. The goal of SVD is to find the best approximation of the original data points in the smallest number of dimensions. This can be accomplished by identifying regions with the highest degree of variability. SVD is used to reduce a big, highly variable set of data points to a lower-dimensional space that more clearly displays the original data's substructure and ranks it from highest to lowest variance. Using the SVD approach, this strategy locates the most variable region and decreases its size. To put it another way, SVD is a data reduction approach.

Numerous eminent mathematicians regard SVD as a crucial topic in linear algebra. Apart from image reduction, SVD is useful in a wide variety of practical and theoretical contexts. The advantage of SVD is that it may be used to any real (m,n) matrix. It divides A into three matrices, U, S, and V, in such a way that

$$A = USV^T$$

S is a diagonal matrix, whereas U and V are orthogonal matrices.

3.2.7. Discrete Cosine Transform (DCT)

A DCT represents the input data points as a sum of cosine functions with various frequencies and magnitudes. The most prevalent DCTs are one-dimensional and two-dimensional. The Joint Photographic Expert Group (JPEG) was founded in 1992 on DCT [14]. It's a common compression method. This is the JPEG method: The initial block size is 8x8. Second, DCT is applied in a left-to-right and top-to-bottom orientation to each block. Then, to limit the amount of data in the memory, quantization is utilized, and data is stored in a precise manner.

3.2.8. Discrete Wavelet Transform (DWT)

The DWT approach is a multi-resolution transform technique that is frequently used to increase the compression ratio of images. This technique uses sub-band coding to represent the signal's time and frequency components. In DWT, a picture is represented by a collection of wavelet functions (also called wavelets) with varying locations and scale [16]. Transform's high pass (detail) and low pass (approximate) coefficients reflect discrete data. 3232 blocks are first partitioned. It divides the data into approximation and detail coefficients. In the rectified matrices, the coefficients are labelled. Then LL is translated to the second level. The compression ratio is obtained by multiplying the coefficients by a predetermined scaling factor.

4. Conclusion:

As there is a trade-off between compression ratio and peak SNR in image compression, developing a more effective compression-decompression technique remains a difficult task in the area. Though considerable research has been conducted in this field, with the ever-increasing demand for low-bit-rate compression methods, there is still room for new approaches and the evolution of more efficient algorithms within existing methods. The review demonstrates that the topic will continue to pique academics' interest in the coming years. We have discussed various types of image compression methods in this article. As a result, we discover that lossy compression provides a higher compression ratio than lossless compression. Compression without loss of data is optimal for text compression. When images have a bit depth greater than 0.5 bpp, all lossy compression algorithms have a high compression ratio. Additionally, image compression is highly dependent on the image's quality.

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