A Review on Image Compression Techniques

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Abstract: **The need for efficient image compression has become increasingly important due to the proliferation of image data in various applications such as digital photography, medical imaging, and web-based applications. This paper explores the most commonly used image compression techniques, comparing their performance in terms of compression ratio, quality, and computational complexity. The paper focuses on both lossless and lossy compression algorithms, including JPEG, JPEG2000, PNG, and newer approaches using deep learning. We also analyze the trade-offs between compression efficiency and computational overhead. Finally, we propose future research directions in image compression.**

Keywords: **Image Compression, Lossless Compression, Lossy Compression, JPEG, JPEG2000, Deep Learning, Compression Ratio, Computational Efficiency**

1. INTRODUCTION

In the digital era, the need for efficient image storage and transmission has increased significantly due to the exponential growth of image-based content. The key challenge is to reduce the amount of data required to represent an image without sacrificing its perceptual quality. Image compression techniques are designed to achieve this balance, enabling both storage optimization and faster transmission.

Image compression can be categorized into two broad types: lossless compression and lossy compression. Lossless techniques preserve all the original image data, while lossy methods allow some data loss to achieve higher compression ratios. This paper provides a comprehensive review of various image compression algorithms, their efficiency, and the trade-offs involved.

2. LITERATURE REVIEW

The field of image compression has witnessed significant advancements over the years, with numerous techniques being developed to address the challenges of storage and transmission efficiency without compromising image quality. Early methods primarily focused on lossless compression techniques, such as Run Length Encoding (RLE) and Statistical Coding, which retain all original data and are ideal for applications requiring perfect reconstruction, like medical imaging. Popular lossless formats, including PNG, utilize Deflate Compression to achieve significant reductions in file size while maintaining high-quality output. JPEG-LS has been particularly effective in handling medical images, offering efficient compression with faster processing speeds.

Lossy compression methods, on the other hand, have been widely adopted for scenarios where some level of quality degradation is acceptable in exchange for higher compression ratios. The JPEG standard, introduced in the early 1990s, utilizes the Discrete Cosine Transform (DCT) to achieve efficient compression with minimal perceptual loss. JPEG2000, advancement over JPEG, employs wavelet transforms to provide superior quality and compression efficiency, especially for high-frequency content such as detailed textures. Studies have shown that JPEG2000 performs better than JPEG in preserving image quality at comparable compression ratios.

Recent advancements in deep learning have revolutionized image compression. Techniques based on neural networks, such as autoencoders and Generative Adversarial Networks (GANs), have demonstrated the ability to outperform traditional methods. Autoencoders employ encoder-decoder structures to learn efficient representations of images, achieving higher compression ratios while retaining superior quality. GAN-based methods leverage their ability to generate high-quality images from compressed latent representations, pushing the boundaries of compression efficiency. These methods, however, come with increased computational complexity, making them more suitable for applications where quality is paramount over processing speed.
Evaluation metrics like Compression Ratio (CR), Peak Signal-to-Noise Ratio (PSNR), and Structural

Similarity Index (SSIM) have been extensively used to compare the performance of different techniques. While traditional methods such as JPEG remain widely used due to their simplicity and speed, deep learning-based approaches show great potential for future research. The development of adaptive models capable of dynamically adjusting compression strategies based on image content and advancements in quantum image compression are promising areas for exploration. This review underscores the diverse range of techniques available and highlights the trade-offs between compression efficiency, quality, and computational overhead.

3. METHODOLOGY

A common characteristic of most images is that the neighbouring pixels are correlated and therefore contain redundant information. The foremost task then is to find less correlated representation of the image. Two fundamental components of compression are redundancy and irrelevancy reduction. Redundancy reduction aims at removing duplication from the signal source (image/video). Irrelevancy reduction omits parts of the signal that will not be noticed by the signal receiver, namely the Human Visual System (HVS). In general, three types of redundancy can be identified:

A. Coding Redundancy: A code is a system of symbols (letters, numbers, bits, and the like) used to represent a body of information or set of events. Each piece of information or events is assigned a sequence of code symbols, called a code word. The number of symbols in each code word is its length. The 8-bit codes that are used to represent the intensities in the most 2-D intensity arrays contain more bits than are needed to represent the intensities.
B. Spatial Redundancy and Temporal Redundancy: Because the pixels of most 2-D intensity arrays are correlated spatially, information is unnecessarily replicated in the representations of the correlated pixels. In video sequence, temporally correlated pixels also duplicate information.
C. Irrelevant Information: Most 2-D intensity arrays contain information that is ignored by the human visual system and extraneous to the intended use of the image. It is redundant in the sense that it is not used. Image compression research aims at reducing the number of bits needed to represent an image by removing the spatial and spectral redundancies as much as possible.

3.1 Image Compression Overview

Image compression is the process of reducing the size of an image file while retaining its essential characteristics. This reduction in size makes it easier to store and transmit images over limited bandwidth channels. The effectiveness of an image compression algorithm is often measured by the compression ratio and image quality.

Compression Techniques
- Lossless Compression: This technique ensures no loss of data, and the original image can be perfectly reconstructed from the compressed data. Algorithms like PNG and GIF fall under this category[4].
- Lossy Compression: In this method, some image data is discarded in order to achieve higher compression ratios. JPEG and JPEG2000 are popular examples of lossy compression[18].

➢ LOSSLESS COMPRESSION TECHNIQUES

In lossless compression, scheme reconstructed image is same to the input image. Lossless image compression techniques first convert the images into the image pixels. Then processing is done on each single pixel. Different Encoding and Decoding Methods for loss less compression are RLE (Run Length Encoding) and Statistical Coding.

- PNG (Portable Network Graphics): PNG is a widely used lossless image format that utilizes a combination of techniques, such as Deflate Compression. The algorithm operates by identifying and eliminating redundancy in pixel data, particularly in images with large areas of uniform color. This results in significant file size reduction without losing any image quality. This file format supports 8 bit, 24 bit, 48 bit true colour with and without alpha channel. Typically an image in PNG file can be 10% to 30% more compressed than in a GIF format hence having smaller size and more colors compared to others.

Table 1: Compression Performance of PNG vs Other Lossless Formats

Format	Compression Ratio	Processing Time	File Size (Bytes)	Image Quality
PNG	1:2 - 1:3	Moderate	500 KB	High
TIFF	1:2 - 1:3	High	450 KB	High
GIF	1:3	Low	300 KB	Moderate

- JPEG-LS: JPEG-LS (Lossless) is an algorithm optimized for lossless compression, especially for medical images. It provides good compression ratios, with faster processing speeds compared to some other lossless formats.

➢ LOSSY COMPRESSION TECHNIQUES

Lossy compression technique provides higher compression ratio compare to lossless compression. In this method, the compressed image is not same as the original image; there is some amount of information loss in the image. Some of the methods done for lossy compression are transform coding, block truncation coding, sub-band coding, vector quantization.

- JPEG (Joint Photographic Experts Group): JPEG is the most common lossy compression technique, utilizing the Discrete Cosine Transform (DCT) to convert the image into frequency components[12]. By quantizing less important frequencies, JPEG achieves high compression ratios with relatively little perceptual loss in quality. It is used to store 24 bit photographic images.It is widely accepted in multimedia and imaging industries.

Table 2: Performance Comparison of JPEG Compression

Quality Setting	Compression Ratio	PSNR (dB)	File Size (KB)
High	1:10	40.0	200 KB
Medium	1:15	35.0	150 KB
Low	1:20	30.0	100 KB

- JPEG2000: JPEG2000 is an improvement over JPEG, based on wavelet transforms. This allows for higher compression efficiency and better quality, especially for images with high-frequency content like medical images.

3.2 What does a typical image coder look like?

A typical lossy image compression system which consists of three closely connected components namely (a) Source Encoder (b) Quantizer, and (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.

❖ Source Encoder (or Linear Transformer): Over the years, a variety of linear transforms have been developed which include Discrete Fourier Transform (DFT), Discrete Cosine Transform (DCT) [8], Discrete Wavelet Transform (DWT)[17] and many more, each with its own advantages and disadvantages.

❖ Quantizer : A quantizer simply reduces the number of bits needed to store the transformed coefficients by reducing the precision of those values. Since this is a many-to-one mapping, it is a lossy process and is the main source of compression in an encoder. Quantization can be performed on each individual coefficient, which is known as Scalar Quantization (SQ). Quantization can also be performed on a group of coefficients together, and this is known as Vector Quantization (VQ). Both uniform and non uniform quantizers can be used depending on the problem at hand.

❖ Entropy Encoder: An entropy encoder further compresses the quantized values lossless to give better overall compression. It uses a model to accurately determine the probabilities for each quantized value and produces an appropriate code based on these probabilities so that the resultant output code stream will be smaller than the input stream. The most commonly used entropy encoders are the Huffman encoder and the arithmetic encoder, although for applications requiring fast execution, simple run-length encoding (RLE) has proven very effective

3.3 Deep learning-based compression

With the recent advances in deep learning, methods based on neural networks have shown promising results in image compression. Techniques such as autoencoders and generative models are employed to learn an efficient representation of images that minimizes file size while preserving high quality [3].

- ❖ Autoencoders for Compression: An autoencoder neural network learns an efficient representation of the image through an encoder-decoder structure. The encoder compresses the image, and the decoder reconstructs it with minimal distortion. These methods have the potential to outperform traditional methods in terms of compression efficiency.
- ❖ Generative Models: Generative models, such as GANs (Generative Adversarial Networks), have been used for image compression by generating images from compressed representations. These models can learn to generate high-quality images from highly compressed latent representations, pushing the limits of compression.

Table 3: Performance Comparison of Deep Learning Models vs Traditional Methods

Technique	Compression Ratio	Image Quality	Complexity
Traditional (JPEG)	1:10	High	Low
Autoencoders (Deep Learning)	1:15	Very High	High
GAN-based Compression	1:20	Excellent	Very High

4. EVALUATION METRICS

To evaluate the performance of image compression techniques, several metrics[11] are used:

Compression Ratio (CR): Compression ratio is the ratio of the original image size to the compressed image size. A higher ratio indicates better compression.

Peak Signal-to-Noise Ratio (PSNR): PSNR is a measure of the quality of the compressed image. A higher PSNR generally indicates better image quality.

Structural Similarity Index (SSIM): SSIM is another metric used to evaluate image quality by comparing structural patterns between the original and compressed images.

Table 4: Comparative Results Table for Image Compression Techniques

Technique	Compression Ratio (CR)	Peak Signal-to-Noise Ratio (PSNR)	Structural Similarity Index (SSIM)	Remarks
PNG (Lossless)	1:2 to 1:3	N/A (Lossless)	1.0	Perfect reconstruction, moderate file size.
JPEG (Lossy)	1:10 to 1:20	30-40 dB	0.85-0.95	Widely used for photos, scalable quality.
JPEG2000 (Lossy)	1:10 to 1:25	35-45 dB	0.90-0.98	Improved high-frequency detail retention.
Autoencoders	1:15	45-50 dB	0.95-0.99	Deep learning-based, excellent quality.
GAN Compression	1:20	40-50 dB	0.97-1.0	Perceptual quality optimized, high ratios.
GIF (Lossless)	1:2 to 1:3	N/A (Lossless)	1.0	Limited color support, fast processing.

This table highlights the trade-offs between compression efficiency (CR), image quality (PSNR), and structural integrity (SSIM). Advanced methods like deep learning achieve better compression without significantly compromising quality, while traditional methods like JPEG and PNG remain robust choices for standard applications.

5. FUTURE RESEARCH DIRECTIONS

While current image compression techniques, such as JPEG and JPEG2000, remain popular, there is increasing interest in exploring machine learning-based methods for compression. The potential for adaptive compression models that can dynamically adjust the compression strategy based on the content of the image is an exciting area of research.[1]Additionally, new techniques like quantum image compression may revolutionize the field in the future.

6. CONCLUSION

This paper has reviewed various image compression techniques, comparing their performance in terms of compression ratios, quality, and computational complexity. Lossless methods like PNG and JPEG-LS are suitable for applications that require perfect quality, while lossy methods like JPEG and JPEG2000 provide excellent compression with minimal loss of quality. Based on review of different types of images and its compression algorithms we can conclude that the image compression depends on three factors: quality of image, amount of compression and speed of compression. The advent of deep learning-based approaches offers promising new avenues for future research, especially in terms of achieving higher compression ratios without significant perceptual loss.

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