



Image Compression: Algorithms, Techniques and Applications

R. S. Bature¹, U. B. Agbala², K. Umar², U.E Okon³

¹Department of Information and Communication Technology,

Nigeria Institute of Leather and Science Technology Zaria, Nigeria

²Department of Computer Science,

Nigeria Institute of Leather and Science Technology, Zaria, Nigeria

³Department of General Studies,

Nigeria Institute of Leather and Science Technology Zaria, Nigeria

ABSTRACT

In the digital age, the proliferation of images necessitates efficient storage and rapid transmission methods to manage the vast amounts of data generated. This paper explores the critical role of image compression, which serves to reduce file sizes while maintaining acceptable quality levels. It distinguishes between two primary types of compression: lossless, which preserves original data integrity, and lossy, which sacrifices some detail for greater size reduction. The reviews of various image compression algorithms, including JPEG and PNG, and highlights advanced techniques such as wavelet transforms and deep learning methodologies that have emerged to address the challenges posed by high-resolution images were also carried out. By examining the strengths and weaknesses of these methods, this paper underscores the importance of ongoing research in image compression to enhance storage efficiency and transmission speed, ultimately contributing to improved user experiences in digital media.

ARTICLE INFO

Article History

Received: October, 2024

Received in revised form: October, 2024

Accepted: December, 2024

Published online: December, 2024

KEYWORDS

Compression, Wavelet, Lossless, Lossy, JPEG

INTRODUCTION

In today's digital age, images play a vital role in our lives. As a result, effective storage and fast transmission of images have become increasingly essential. Image compression offers a solution to these challenges, enabling images to be transmitted quickly online while utilizing limited storage capacity. Recent advancements in the field of digital imaging have made image compression a popular research area. Research in image compression primarily focuses on developing algorithms that reduce file sizes without compromising image quality (Liu *et al.*, 2017; Zakhor *et al.*, 2018; Burger & Burger 2020). These algorithms employ various techniques, each with practical applications that impact storage and transmission efficiency. The challenge of balancing file size and image quality is a central issue in image compression. Compressing data reduces storage and transmission requirements but inevitably leads to a loss of detail. There are two primary types of

compression: lossless and lossy (Hu *et al.*, 2021; Kaushik 2024). Lossy compression discards data during compression, making it impossible to fully recover the original image. In contrast, lossless compression ensures that the original data can be restored without loss (Mentzer 2024). Achieving high-quality image compression is a complex issue in a rapidly evolving field. To appreciate the strengths and weaknesses of different compression methods, it is essential to understand various techniques. This paper discusses several algorithms, techniques, and their practical applications, highlighting the uses of image compression in subsequent sections.

FUNDAMENTALS OF IMAGE COMPRESSION

Understanding the fundamentals of image compression is crucial due to its significant impact on key image characteristics and human visual perception. Image compression optimizes the use of costly transmission and storage resources by reducing image data size. This

Corresponding author: R. S. Bature

✉ rsbature@gmail.com

Department of Information and Communication Technology, Nigeria Institute of Leather and Science Technology, Zaria.

© 2024. Faculty of Technology Education. ATBU Bauchi. All rights reserved

enables the representation of images with fewer bits, maintaining a specified quality or resolution. The most basic form of image compression involves reducing pixel quality, thereby decreasing redundancy. Early encoding techniques employed this approach, compressing small images (e.g., 32x16 pixels) or discarding imperceptible data like brightness distributions.

Uncompressed images require substantial memory and storage space, resulting

in prolonged transmission times between devices. As illustrated in Table 1, the size difference between uncompressed text and highly compressed images is substantial. This highlights the need for sufficient storage space and increased bandwidth to mitigate lengthy transmission times. Consequently, image compression is essential to address these challenges.

Table 1: Requirements for Uncompressed Multimedia Data

Multimedia Data	Image size	Bits per pixels (bpp) or Bits per sample (bps)	Uncompressed size (B=Bytes)	Transmission Bandwidth (b=bits)	Transmission Time
A page of text	11"x8.5"	Depends on resolution	4.8KB	32.64 Kb/page	1.2-2.4 sec
Telephone quality speech	10 sec	8 bps	80 KB	64 Kb/sec	22.2 sec
Colour image	512x512	24 bpp	786 KB	6.29 Mb/image	3 min 39 sec
Medical image	2048x1680	12 bpp	5.16 MB	41.3 Mb/image	23 min 54 sec

The examples presented in Table 1 highlight the necessity for substantial storage space, extensive transmission bandwidth, and prolonged transmission times for image, audio, and video data. Given the current state of technology, compressing multimedia data prior to storage and transmission, and then decompressing it at the receiver for playback, is the only viable solution. For instance, achieving a compression ratio of 32:1 can reduce storage, bandwidth, and transmission time requirements by a factor of 32, while maintaining acceptable quality.

The image compression system comprises two primary components: the compressor and the decompressor. The compressor consists of two stages: preprocessing and encoding. Conversely, the decompressor involves two stages: decoding and post processing. A detailed illustration of the compression process is provided in Figure 1. Prior to encoding, preprocessing is conducted to prepare the image for encoding. This stage encompasses various application-specific operations. Following decoding, post processing can be performed to mitigate undesirable artifacts introduced during compression.

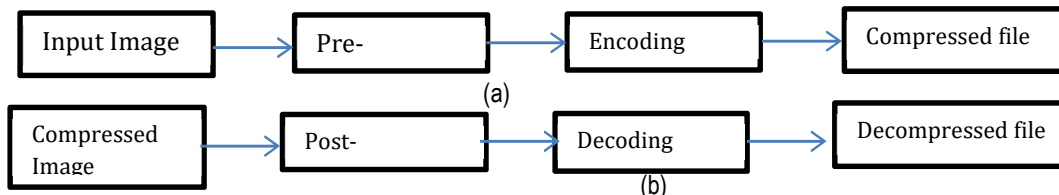


Figure 1: Compression and Decompression system model

Corresponding author: R. S. Bature

rsbature@gmail.com

Department of Information and Communication Technology, Nigeria Institute of Leather and Science Technology, Zaria.

© 2024. Faculty of Technology Education. ATBU Bauchi. All rights reserved

Prior to the encoding as shown in Figure 1, preprocessing is conducted to prepare the image for encoding. This stage encompasses various application-specific operations. The reduced file which is thus, created by the compression process is called the *compressed file* and is used to reconstruct the image, resulting in the *decompressed image*. The ratio of the original/input image (uncompressed file) and the compressed file is referred to as the *compression ratio*. The compression ratio can be expressed as:

$$\text{Compression ratio} = \frac{\text{Uncompressed file size}}{\text{Compressed file size}} \quad (1)$$

Image compression are categories into two: lossy compression and lossless compression. These two categories of compression are discussed in the next subsection.

Lossy vs. Lossless Compression

In lossy compression, some of the data from the original file is removed for a smaller file size. However, this kind of compression reduces the quality, and the file cannot be restored to its original state. On the other hand, lossless compression can reduce the file to a smaller size without affecting the image quality (Adedokun *et al.*, 2019; Momoh *et al.*, 2019). However, the restored file is totally unmodified in image quality and resolution of the original file.

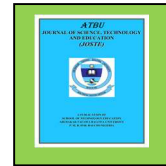
In most image compression applications, the objective is to minimize the largest case of distortion. Thus, when judging the quality of a compression scheme, this measure of distortion is used. Lossless compression algorithms do not reduce the quality of the image in any way. However, lossy compression algorithms remove some image data in order to reduce file size. There is always a trade-off between the amount of compression and image quality, which makes the distinction between lossy and lossless methods very important, especially in specific applications. The image storage requirements are reduced as the compression ratio increases. The distinction between the lossy and lossless methods can be made based on the

application requirements, cost, and system performance. A good example of a lossy compression application is the storing of images on compact digital cameras, such as the one in a cellular phone, where the enlargement of the image is not a critical factor (Momoh *et al.*, 2020). Conversely, a good example of a lossless compression application is image archive storage or any medical applications where the image enlargement is important after decompression.

Spatial vs. Transform Coding

The coding in image compression can be categorized into two primary classes: spatial coding, where the coding is performed on the pixel values, and transform coding, where the image data are first converted from the spatial domain into another domain in which the image is analyzed and compressed. Spatial coding depends on the redundancy within the image data. Since the pixel data in images are usually correlated, especially in the neighboring pixels, it takes advantage of such redundancy and thereby achieves compression (Zhang *et al.*, 2020). This is done using various techniques such as run-length coding, predictive coding, and differential pulse code modulation. Transform coding, however, takes advantage of the fact that the energy in the image is compact and most of it is concentrated at the lowest frequencies because of the smooth intensity changes between neighboring pixels, while high frequencies are usually caused by abrupt intensity variations (Bi *et al.*, 2015; Zhang *et al.*, 2020).

Since the major portion of the image is associated with low frequencies, these low frequencies can be coded with fewer bits than required for coding high frequencies. Since the frequency content of the images does not change, transform coding can achieve greater compression. The transformation allows for the temporary decorrelation of pixel data, which speeds up the entropy coding. All image blocks (or the entire image) will have the highest entropy before entropy coding is applied. Some of the popular examples are DCT, Fourier series transform, K-L transform, and Hadamard transform. The commonly known algorithm for



transform coding is the Modified Discrete Cosine Transform. The overall aspect of transform coding provides accuracy and insensitivity to transformation or scaling when data are more correct. The limitations here are time complexity and rounding errors. In most real-world practical image compression, the coding is a mix of spatial and transform coding, where transform coding helps subsequently in the coding of the boundary regions of the images.

Popular Image Compression Algorithms

Image compression algorithms are essential in various industrial applications. This section introduces two widely used image compression algorithms: JPEG and PNG.

JPEG Compression

The JPEG standard is a lossy and popular compression technique. The JPEG is designed to support up to 24 bits per pixel. The image compression algorithm of JPEG consists of many intricate steps. The core of the JPEG image compression process is based on the Discrete Cosine Transform (Skodras *et al.*, 2001). For each whole image, the JPEG image compression technique reduces its size into acceptable lossy sizes. The JPEG image compression has many settings to balance between the quality of the images and the size of the image files. The color quality of the JPEG images starts to degrade at around 85% compression level. JPEG lossy compression is ideal for web images and photography. Some of the common applications to use JPEG are web images and email, below 60% of quality setting. The first JPEG group was founded in 1986, and it soon turned out to be the world's most widely used imaging-based design. JPEG standards till date still rank among the most popular internet applications. The JPEG format, used for the vast majority of continuous and still photographic images on the internet, has revolutionized the printing and film industries. The JPEG software can be easily read and used by thousands of people worldwide.

PNG Compression

PNG (Portable Network Graphics) is a lossless image format that supports an 8-bit alpha

channel to allow translucency or 1-bit alpha for fully opaque or fully transparent images. A significant advantage of PNGs is that, it contain up to 48-bit true color information yet don't use a palette. This gives them greater color fidelity over JPEG images. Moreover, the format has no (or very little) artifacting or distortion due to lossy compression. PNGs use approximately 20–40%. PNGs are suitable for saving images without a dramatic loss of quality or for web pages that need to save images without using the GIF format. Both the IHDR chunk, which contains the header information, and an IEND chunk, which proclaims the end of the file, are in every image file. No other chunks are required, but in a typical file, there will be additional chunks for Palette, Transparency, and Image data. Like GIF, PNG supports index transparency (Skodras *et al.*, 2001).

Advanced Techniques in Image Compression

The widespread adoption of high-resolution cameras has created a pressing need for advanced image compression methods. In response, wavelet techniques and deep learning methodologies have emerged as promising solutions, offering efficient and effective ways to compress high-quality images. The following subsection delves into the wavelet transform and deep learning approaches to image compression.

Wavelet Transform

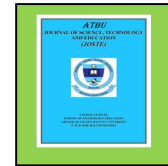
Wavelets constitute a set of basis functions that have become increasingly popular in image processing due to their multiresolutional analysis capabilities. In the context of image processing and compression, they have a variety of properties that make them distinct from other transform methods discussed. Traditional transform coding methods encounter inefficiencies when dealing with human-perceived data rates, as they are only capable of reducing the spatial redundancy aspect of the image, while the spectral redundancy aspect is left untouched. Wavelets, however, do not conform to the rectilinear structure of data when transformed by classical techniques and are better at representing an image's rough and fine details at different scales, resulting in a more compact representation

Corresponding author: R. S. Bature

✉ rsbature@gmail.com

Department of Information and Communication Technology, Nigeria Institute of Leather and Science Technology, Zaria.

© 2024. Faculty of Technology Education. ATBU Bauchi. All rights reserved



of data and therefore making it more efficient in representing an image. Most energy in an image, or any other signal, is concentrated at low frequencies. When transformed to the wavelet domain, signals are dysfunctional in recording the fluctuating position of high frequency in contrast to low frequency. This makes wavelets very effective at 'compressing' data and achieving a lower compression ratio and an image of high quality. A variety of algorithms have emerged that utilize wavelet functions for compression purposes. Haar, Daubechies, and Cohen-Daubechies-Feauveau are among the popular wavelet techniques. Wavelets and subband coding algorithms have a sound theoretical foundation and have been implemented in many practical codes and standards (Oliver-Gil 2008; Gazal et al., 2020). Generally, wavelet transform (or associated subband transform) produces significantly better subjective image quality compared to other transform coding algorithms. Consequently, interest in wavelet subband approaches to image compression techniques is renewed. Subband coding methods were developed after the advent and success of transform coding schemes in order to address some of the limitations and problems with these conventional methods. Subband coding is also known as filter bank coding, which inherits the basis of transform coding and is equivalent to transform coding when implemented as a critically sampled system. A significant advantage of subband coding methods is that they allow for modularity of the coding system with the decomposition process, which allows for a variety of data from the transformed subband to be effectively quantized, thereby increasing the encoding efficiency. However, wavelets have not been widely accepted until about the last decade.

Deep Learning Approaches

Deep learning neural networks have revolutionized image compression, enabling progressive improvements in compression efficiency while minimizing quality loss. Among various techniques, deep learning stands out as the most promising approach to enhance the compression process. By leveraging deep digital

neural networks, it is possible to achieve better compression ratios while preserving image quality, thereby pushing the boundaries of image compression capabilities. The deep convolutional neural network (CNN) technique is a notable solution, specifically designed for image signal processing. This approach has yielded promising results, as demonstrated by numerous experiments across various scenarios and applications. For instance, a deep learning approach was proposed for traffic camera image compression, leveraging a database of images captured under diverse environmental conditions. The growing interest in deep learning, combined with the success of CNNs in image processing, has led to the development of image compression techniques based on deep learning (Abd-Alzhra & Al-Tamimi 2022). These techniques can be broadly categorized into three types: classification-based, autoencoder-based, or a combination of both. While CNN-based image compression can produce high-quality outputs, one of the key challenges is acquiring sufficient training data. The training process, particularly with regard to compression distortion, is more complex than training CNNs for classification tasks. Other JPEG-based methods have been adopted in real-world applications, but they pose challenges, such as training models and requiring substantial computational resources. Despite these challenges, deep learning-based image compression techniques hold significant promise for achieving improved compression ratios while maintaining image quality.

Applications of Image Compression

Image compression plays a vital role in various applications, particularly in the era of digital photography and medical imaging.

Digital Photography

Digital photography has become increasingly popular, resulting in a massive surge in the number of images captured. Image compression algorithms, such as JPEG, have enabled efficient storage and transfer of these images. Photographers can choose from various

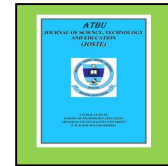


image quality settings and color spaces, including RGB, YUV, $L_a_b^*$, XYZ, and YCbCr.

The use of image compression in digital photography offers several benefits, including reduced storage costs and enhanced communication among photographers. However, repetitive compression can affect image authenticity. Social media applications often employ low-quality image compression to facilitate faster transmission and display (Parulski & Rabbani 2000).

Medical Imaging

Medical imaging is another significant application of image compression. Medical images, such as MRI and CT scans, require high-quality preservation to ensure accurate diagnosis. Lossy compression can compromise image quality, while lossless compression is often preferred. The compression of medical images is crucial for efficient storage, transmission, and retrieval. Image compression algorithms must balance compression ratios with diagnostic accuracy. Advanced image processing tools contribute significantly to medical diagnosis, and efficient compression algorithms are essential for medical imaging datasets.

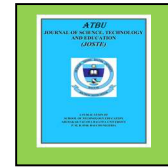
Medical imaging applications, such as telemedicine and telepathology, rely heavily on image compression to facilitate the transmission and storage of large medical image files. The use of image compression in medical imaging has become increasingly important, enabling healthcare professionals to access and share medical images efficiently (Monika & Dhanalakshmi 2023).

CONCLUSION

Image compression is an essential technology that addresses the challenges of data storage and transmission in an increasingly image-centric world. The balance between file size and image quality remains a central concern, with various algorithms offering distinct advantages depending on the application. Lossy compression techniques, such as JPEG, are widely used for web images and photography, while lossless methods like PNG are preferred for

applications requiring high fidelity. The advent of advanced techniques, including wavelet transforms and deep learning, presents promising avenues for future research and development, enabling more efficient handling of high-resolution images. As technology continues to evolve, the need for effective image compression solutions will only grow, making it imperative for researchers and practitioners to innovate and refine these methods to meet the demands of modern digital communication.

- REFERENCES** Abd-Alzhra, A. S., & Al-Tamimi, M. S. (2022). Image compression using deep learning: methods and techniques. *Iraqi Journal of Science*, 1299-1312.
- Adedokun, A. E., Abdulrazak, M. B., Omuya, M. M., Bello-Salau, H., & Sadiq, B. O. (2019). A spatio-temporal based frame indexing algorithm for qos improvement in live low-motion video streaming. *ATBU Journal of Science, Technology and Education*, 7(3), 305-315.
- Bi, S., Han, X., & Yu, Y. (2015). An l1 image transform for edge-preserving smoothing and scene-level intrinsic decomposition. *ACM Transactions on Graphics (TOG)*, 34(4), 1-12.
- Burger, W., & Burge, M. J. (2022). *Digital image processing: An algorithmic introduction*. Springer Nature.
- Gazal, O. M., Adedokun, A. E., Umoh I. J., Momoh M. O., (2020). LWT-CLAHE Based Color Image Enhancement Technique: An Improved Design. *Computer Engineering and Applications Journal*, 9(2), 117-126.
- Hu, Y., Yang, W., Ma, Z., & Liu, J. (2021). Learning end-to-end lossy image compression: A benchmark. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 44(8), 4194-4211.
- Hussain, A. J., Al-Fayadh, A., & Radi, N. (2018). Image compression techniques: A survey in lossless and lossy



- algorithms. *Neurocomputing*, 300, 44-69.
- Kaushik, B. (2024). Efficient Compression Techniques for Medical Image Storage and Transmission: A Comprehensive Review. *International Journal of Image and Graphics*, 2650024.
- Liu, F., Hernandez-Cabronero, M., Sanchez, V., Marcellin, M. W., & Bilgin, A. (2017). The current role of image compression standards in medical imaging. *Information*, 8(4), 131.
- Mentzer, F. (2021). *Neural Image Compression: Lossy and Lossless Algorithms* (Doctoral dissertation, ETH Zurich).
- Momoh, M. O., Ndunagu, J. N., Abanihi, V. K., Yusuf, S. M., & Abdullah, M. I. (2020). A Comparative Analysis of Video Compression Standard and Algorithms: State of the Art. *ATBU Journal of Science, Technology and Education*, 8(2), 181-188.
- Momoh, M. O., Yahaya, B., Abdulrazaq A. A., Katagum, H. M., & Abubakar U. (2019). Towards achieving an optimal bandwidth utilization in live video streaming. Academic Conference on 21st Century Challenges and Opportunities: Multi-disciplinary Approaches. 19(3) 55-61.
- Monika, R., & Dhanalakshmi, S. (2023). An efficient medical image compression technique for telemedicine systems. *Biomedical Signal Processing and Control*, 80, 104404.
- Oliver-Gil, J. S. (2008). *On the design of fast and efficient wavelet image coders with reduced memory usage* (Doctoral dissertation, Universitat Politècnica de València).
- Parulski, K., & Rabbani, M. (2000, May). The continuing evolution of digital cameras and digital photography systems. In *2000 IEEE International Symposium on Circuits and Systems (ISCAS)* (Vol. 5, pp. 101-104). IEEE.
- Skodras, A., Christopoulos, C., & Ebrahimi, T. (2001). The JPEG 2000 still image compression standard. *IEEE Signal processing magazine*, 18(5), 36-58.
- Zakhor, A., Barni, M., Mitra, S. K., Ostermann, J., Vetro, A., Hamzaoui, R., & De Queiroz, R. L. (2018). *Document and Image compression*. CRC press.