



Review Paper on Lossy Image Compression using Discrete Wavelet Transform and Coding Technique

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Abstract

Lossy image compression plays a crucial role in reducing storage requirements and transmission bandwidth while maintaining acceptable visual quality. Among various compression techniques, the Discrete Wavelet Transform (DWT) has emerged as a powerful tool due to its ability to provide multi-resolution representation and superior energy compaction. This review paper presents a comprehensive analysis of lossy image compression methods based on DWT combined with advanced coding techniques. The study explores the fundamental principles of wavelet decomposition, including sub-band coding and hierarchical representation of image data. It further examines prominent coding approaches such as Embedded Zerotree Wavelet (EZW), Set Partitioning in Hierarchical Trees (SPIHT), and Embedded Block Coding with Optimized Truncation (EBCOT), highlighting their efficiency in achieving high compression ratios with minimal perceptual loss. Additionally, the paper compares the performance of these techniques using key evaluation metrics such as Peak Signal-to-Noise Ratio (PSNR), Mean Squared Error (MSE), and compression ratio. Recent advancements integrating machine learning and hybrid optimization strategies with DWT-based compression are also discussed to demonstrate improvements in reconstruction quality and computational efficiency. The review identifies challenges such as artifact reduction, edge preservation, and real-time implementation constraints, and outlines future research directions in adaptive wavelet selection and intelligent coding frameworks. Overall, this paper provides valuable insights into the evolution and effectiveness of DWT-based lossy image compression techniques for modern multimedia applications.

Keywords: Discrete Wavelet Transform (DWT), Lossy Image Compression, Wavelet Decomposition, Peak Signal-to-Noise Ratio (PSNR), Mean Squared Error (MSE), Compression Ratio

I. INTRODUCTION

In the modern digital era, the rapid growth of multimedia applications such as medical imaging, satellite communication, video streaming, and social media has led to an exponential increase in the volume of image data. Efficient storage and transmission of such large datasets have become a significant challenge, making image compression an essential area of research. Image compression techniques aim to reduce the redundancy present in image data while preserving



the perceptual quality of the reconstructed image. Among the various types of compression, lossy image compression is widely adopted due to its ability to achieve high compression ratios by allowing a controlled loss of information that is often imperceptible to the human visual system [1, 2].

Traditional compression methods, such as those based on the Discrete Cosine Transform (DCT), have been extensively used in standards like JPEG. However, these methods suffer from limitations such as blocking artifacts, especially at higher compression ratios. To overcome these issues, transform-based techniques using the Discrete Wavelet Transform (DWT) have gained considerable attention. DWT provides a more efficient representation of image data by decomposing an image into different frequency sub-bands, enabling multi-resolution analysis. This property allows the separation of important image features such as edges and textures, which are crucial for maintaining visual quality after compression.

The Discrete Wavelet Transform works by passing the image through a series of low-pass and high-pass filters, resulting in sub-bands that represent different levels of detail. These sub-bands include approximation and detail components, which can be further decomposed to achieve higher levels of resolution. This hierarchical structure makes DWT particularly suitable for progressive image transmission and scalable compression. Furthermore, DWT-based methods reduce blocking artifacts and provide better energy compaction compared to traditional techniques, making them more efficient for modern image compression applications [3, 4].

In addition to transform techniques, coding plays a vital role in achieving efficient compression. Advanced coding algorithms such as Embedded Zerotree Wavelet (EZW), Set Partitioning in Hierarchical Trees (SPIHT), and Embedded Block Coding with Optimized Truncation (EBCOT) have been developed to exploit the statistical properties of wavelet coefficients. These coding methods efficiently encode significant coefficients while discarding redundant or less important information, thereby improving compression performance. Among these, SPIHT and EBCOT are widely recognized for their superior rate-distortion performance and have been incorporated into standards such as JPEG2000 [5].

Recent advancements in image compression have focused on integrating DWT with machine learning and optimization techniques to further enhance performance. Hybrid approaches aim to improve compression efficiency, reduce computational complexity, and preserve image quality. Additionally, research efforts are being directed toward addressing challenges such as edge preservation, noise reduction, and real-time processing for high-resolution images [6, 7].

This review paper aims to provide a comprehensive overview of lossy image compression techniques based on the Discrete Wavelet Transform and various coding strategies. It discusses the fundamental concepts, compares different methods based on performance metrics, and highlights recent developments in the field. The paper also identifies existing challenges and suggests potential directions for future research. Through this analysis, the study seeks to contribute to the understanding and advancement of efficient image compression techniques for emerging multimedia applications.



II. LITERATURE SURVEY

Shiju Thomas et al. [1], proposed a novel image compression method that integrates wavelet coefficients with Huffman coding to enhance compression efficiency. Their approach leverages the multi-resolution capability of the Discrete Wavelet Transform (DWT) to decompose images into different frequency components, followed by entropy-based Huffman coding to reduce redundancy. The study demonstrated that combining wavelet-based transformation with statistical coding significantly improves compression ratio while maintaining acceptable image quality. The results highlighted improved Peak Signal-to-Noise Ratio (PSNR) and reduced Mean Squared Error (MSE), making the technique suitable for applications requiring efficient storage and transmission. However, the method still faces challenges related to computational complexity when dealing with high-resolution images.

R. A. Elsayw et al. [2], introduced an optimized end-to-end compression framework using Coiflets-based Discrete Wavelet Transform specifically for dermoscopic images. Their research focused on medical image compression, where preserving fine details is critical for diagnosis. By optimizing wavelet filter selection and incorporating efficient encoding strategies, the proposed method achieved superior compression performance compared to conventional techniques. The study reported enhanced visual quality and higher PSNR values, indicating its effectiveness in preserving diagnostically relevant features. Additionally, the approach addressed noise sensitivity and improved robustness, although it required careful parameter tuning for different datasets.

A. Jeromel et al. [3], conducted a comparative study of entropy coders for lossless grayscale image compression. Although the work primarily focused on lossless techniques, it provided valuable insights into the efficiency of different entropy coding schemes, such as Huffman coding, arithmetic coding, and Golomb coding. The authors evaluated performance based on compression ratio and computational efficiency, concluding that arithmetic coding often outperforms traditional methods in terms of compression efficiency. This study is relevant to lossy compression frameworks as entropy coding forms a crucial final stage in many hybrid systems, including DWT-based compression techniques.

X. Liu et al. [4], proposed an improved lossless image compression algorithm based on Huffman coding. Their approach introduced modifications in symbol encoding and probability estimation to enhance compression performance. The experimental results showed improved compression ratios compared to conventional Huffman coding, while maintaining low computational complexity. Although primarily designed for lossless compression, the study contributes to the understanding of efficient entropy coding mechanisms that can be integrated into lossy frameworks such as DWT-based systems.

N. Brahimi et al. [5], presented a lossy image compression technique based on an efficient multiplier-less 8-point Discrete Cosine Transform (DCT). The proposed method aimed to reduce hardware complexity and power consumption while maintaining compression performance. By eliminating multipliers, the algorithm achieved faster processing suitable for real-time applications. However, despite its efficiency, DCT-based methods are still prone to



blocking artifacts, which limits their performance compared to wavelet-based techniques. This highlights the advantage of DWT in providing smoother image reconstruction and better visual quality.

Y. Hu et al. [6], explored end-to-end learning-based lossy image compression using deep neural networks. Their work established a benchmark for comparing traditional compression techniques with modern deep learning approaches. The study demonstrated that learning-based methods can outperform conventional transform-based techniques in terms of rate-distortion performance. However, these methods require large training datasets and high computational resources, making them less practical for certain real-time or resource-constrained applications. Nevertheless, the integration of machine learning with DWT-based methods presents a promising direction for future research.

Shuyuan Zhu et al. [7], proposed a compression-dependent transform domain downward conversion technique for block-based image coding. Their approach focused on optimizing transform-domain processing to improve compression efficiency while maintaining image quality. The study introduced adaptive strategies that adjust compression parameters based on image characteristics, resulting in improved rate-distortion performance. This work provides valuable insights into adaptive compression techniques that can be combined with wavelet-based frameworks.

Julio Cesar et al. [8], investigated data compression techniques for smart distribution systems using Singular Value Decomposition (SVD). Although the focus was on power system data, the study demonstrated the effectiveness of matrix decomposition techniques in reducing data redundancy. The results showed that SVD-based compression can achieve significant data reduction while preserving essential information. This approach highlights alternative mathematical techniques that can complement wavelet-based image compression methods.

Sunwoong Kim et al. [9], proposed an RGBW image compression method using low-complexity adaptive multi-level Block Truncation Coding (BTC). Their approach aimed to reduce computational complexity while maintaining acceptable image quality. The adaptive multi-level strategy improved compression efficiency compared to traditional BTC methods. However, the method is less effective in preserving fine image details compared to transform-based techniques like DWT, which offer better frequency-domain representation.

C. Senthil Kumar et al. [10], introduced an enhanced Block Truncation Coding (E-BTC) scheme for color and multispectral image compression. The proposed method improved upon traditional BTC by incorporating advanced encoding strategies to enhance image quality and compression ratio. The study demonstrated better performance in terms of visual quality and computational efficiency. Despite these improvements, BTC-based methods still lag behind wavelet-based techniques in terms of scalability and multi-resolution representation, reinforcing the importance of DWT in modern image compression research.

Methodology

• Discrete Wavelet Transform

Wavelets are signals which are local in time and scale and generally have an irregular shape. A wavelet is a waveform of effectively limited duration that has an average value of zero. The term ‘wavelet’ comes from the fact that they integrate to zero; they wave up and down across the axis. Many wavelets also display a property ideal for compact signal representation: orthogonality. This property ensures that data is not over represented. A signal can be decomposed into many shifted and scaled representations of the original mother wavelet. A wavelet transform can be used to decompose a signal into component wavelets. Once this is done the coefficients of the wavelets can be decimated to remove some of the details. Wavelets have the great advantage of being able to separate the fine details in a signal. Very small wavelets can be used to isolate very fine details in a signal, while very large wavelets can identify coarse details. In addition, there are many different wavelets to choose from. Various types of wavelets are: Morlet, Daubechies, etc. [8].

This technique first decomposes an image into coefficients called sub-bands and then the resulting coefficients are compared with a threshold. Coefficients below the threshold are set to zero. Finally, the coefficients above the threshold value are encoded with a loss less compression technique. The compression features of a given wavelet basis are primarily linked to the relative scarceness of the wavelet domain representation for the signal. The notion behind compression is based on the concept that the regular signal component can be accurately approximated using the following elements: a small number of approximation coefficients (at a suitably chosen level) and some of the detail coefficients [9, 10].

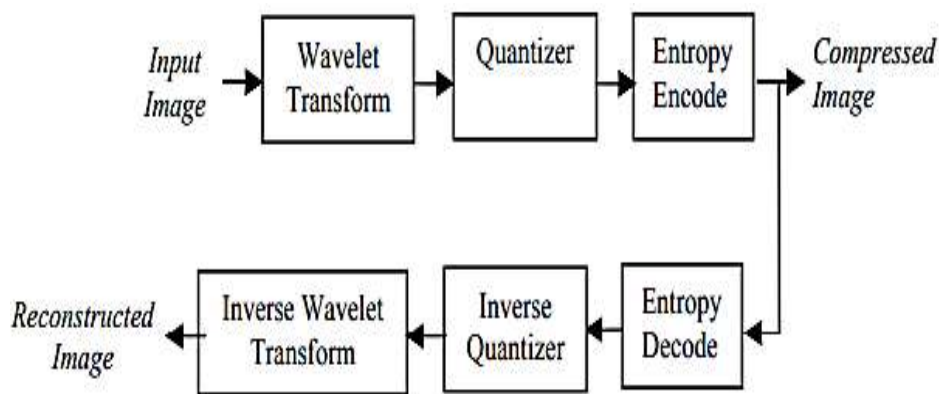


Figure 1: The structure of the wavelet transform based compression

The steps of compression algorithm based on DWT are described below:

- I. Decompose Choose a wavelet; choose a level N. Compute the wavelet. Decompose the signals at level N.
- II. Threshold detail coefficients For each level from 1 to N, a threshold is selected and hard thresholding is applied to the detail coefficients.

III. Reconstruct Compute wavelet reconstruction using the original approximation coefficients of level N and the modified detail coefficients of levels from 1 to N.

- **Multi-level Block Truncation Code**

The Encoder and decoder block of the multi-level block truncation code algorithm is shown in figure 2. Encoder part of the proposed algorithm shows that the original image is divided into three parts i.e. R component, G component and B component. Each R, G, B component of the image is divided into non overlapping block of equal size and threshold value for each block size is being calculated.

Threshold value means the average of the maximum value (max) of 'k × k' pixels block, minimum value (min) of 'k × k' pixels block and m_1 is the mean value of 'k × k' pixels block. Where k represents block size of the color image. So threshold value is:

$$T = \frac{\max + \min + m_1}{3}$$

(1)

Each threshold value is passing through the quantization block. Quantization is the process of mapping a set of input fractional values to a whole number. Suppose the fractional value is less than 0.5, then the quantization is replaced by previous whole number and if the fractional value is greater than 0.5, then the quantization is replaced by next whole number.

Each quantization value is passing through the bit map block. Bit map means each block is represented by '0' and '1' bit map. If the Threshold value is less than or equal to the input image value then the pixel value of the image is represented by '0' and if the threshold value is greater than the input image value then the pixel value of the image is represented by '1'.

Bit map is directly connected to the high and low component of the proposed decoder multi-level BTC algorithm. High (H) and low (L) component is directly connected to the bit map, bitmap converted the '1' and '0' pixel value to high and low pixel value and arrange the entire block.

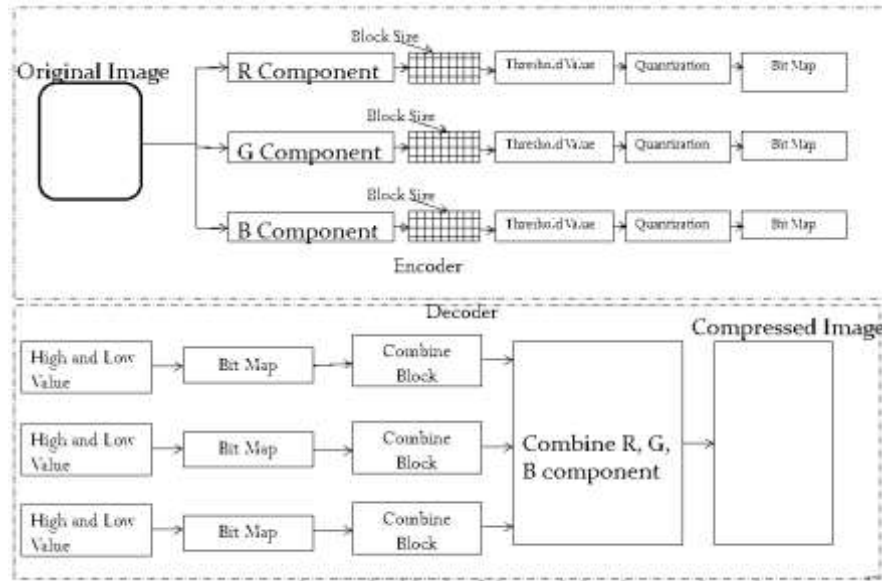


Figure 2: Block Diagram of Proposed Algorithm

$$L = \frac{1}{q} \sum_{i=1}^p W_i \quad W_i \leq T$$

(2)

$$H = \frac{1}{p} \sum_{i=1}^p W_i \quad W_i > T$$

(3)

W_i represent the input color image block, q is the number of zeros in the bit plane, p is the number of ones in the bit plane. In the combine block of decoder, the values obtained from the pattern fitting block of individual R, G, B components are combined after that all the individual combined block are merged into a single block. Finally compressed image and all the parameter relative to that image will be obtained.

• **Discrete Cosine Transform**

A discrete cosine transform (DCT) express a finite sequence of data points in expressions of a sum of cosine functions oscillating at different frequencies. DCTs are mainly important to numerous applications in science and engineering, from lossy compression of audio(e.g.-MP3) and image(e.g. JPEG) (where small and high frequency components can be rejected), to spectral method for the numerical solution of partial differential equations. The use of cosine function instead of sine is critical for compression, since it turns out (as explained below) that



fewer cosine functions are required to approximate a typical signal, where for differential equations cosines function express a particular choice of boundary conditions.

- **Error-compensated scalar quantization**

The application of ICDF in the TDDC-based coding aims at a better interpolation and a lower compression cost. However, when the compression happens, the interpolation efficiency as well as the coding efficiency will be limited by the distortion occurring on those filtered pixels (denoted as $\sim x$) that will be used for interpolation. To solve this problem, we purpose to reduce the sum of square error (SSE) distortion of $\sim x$ as much as possible via controlling the quantization error of the transformed macro-block based on an error-compensated scalar quantization (ECSQ).

III. CONCLUSION

This review paper has presented a comprehensive analysis of lossy image compression techniques with a primary focus on the Discrete Wavelet Transform (DWT) and associated coding methods. The study highlights that DWT-based compression offers significant advantages over traditional techniques, particularly in terms of multi-resolution analysis, energy compaction, and reduced blocking artifacts. By decomposing images into different frequency sub-bands, DWT enables efficient representation and selective encoding of important visual information, which results in improved compression performance and better reconstructed image quality.

The review of various coding techniques, including Embedded Zerotree Wavelet (EZW), Set Partitioning in Hierarchical Trees (SPIHT), Embedded Block Coding with Optimized Truncation (EBCOT), and Huffman coding, demonstrates that the integration of transform and efficient encoding schemes plays a crucial role in achieving high compression ratios with minimal perceptual loss. Among these, SPIHT and EBCOT have shown superior rate-distortion performance and are widely used in practical applications such as JPEG2000. Additionally, comparisons with other approaches such as Discrete Cosine Transform (DCT), Block Truncation Coding (BTC), and Singular Value Decomposition (SVD) indicate that wavelet-based methods consistently outperform traditional techniques in terms of visual quality and scalability.

Furthermore, recent advancements in machine learning and deep learning-based compression techniques have introduced new possibilities for improving compression efficiency and adaptability. These methods demonstrate enhanced performance in terms of rate-distortion optimization; however, they also introduce challenges such as high computational complexity and the need for large training datasets. Hybrid approaches that combine DWT with intelligent algorithms are emerging as promising solutions to balance performance and efficiency.

Despite significant progress, several challenges remain in the field of lossy image compression. Issues such as edge preservation, artifact reduction, real-time processing, and hardware implementation constraints continue to require further research. Future work should focus on adaptive wavelet selection, optimization of coding strategies, and integration of lightweight machine learning models to enhance performance in resource-constrained environments.



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