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Efficient Image Compression Using Discrete Wavelet Transform and Global Thresholding

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ABSTRACT
This paper presents an efficient image compression technique based on the Discrete Wavelet Transform (DWT) coupled with a global thresholding strategy to optimize data reduction while maintaining structural fidelity. The proposed approach decomposes spatial data into multi-resolution sub-bands to systematically isolate significant coefficients from low-energy, redundant details. A unified global thresholding matrix is then applied across the wavelet domain, eliminating non-essential coefficients to minimize storage footprints. MATLAB simulations evaluate the framework using Peak Signal-to-Noise Ratio (PSNR) and Mean Squared Error (MSE) metrics across varying wavelet families (DB7 and DB1). Experimental results demonstrate that higher-order Daubechies filters achieve superior energy compaction, yielding excellent reconstruction quality (e.g., PSNR of 36.21 dB) with low computational complexity. The study validates this framework as a practical, low-overhead solution for high-fidelity multimedia storage and transmission applications.
Keywords: *Discrete Wavelet Transform (DWT), Image Compression, Global Thresholding, Daubechies Wavelets, Multi-Resolution Analysis, Peak Signal-to-Noise Ratio (PSNR), Energy Compaction.*

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I. INTRODUCTION

The rapid growth of computer processing power and digital communication technologies has significantly increased the importance of data compression, especially in multimedia applications. Image compression plays a crucial role in reducing the storage requirements of digital images and improving the efficiency of data transmission over communication networks. This is particularly important in modern networked systems where bandwidth is limited and large volumes of visual data must be transmitted efficiently [1-2]. By reducing file size, compression techniques help optimize the use of available storage resources and decrease transmission time and cost. Digital image compression involves reducing the size of image data while preserving acceptable visual quality. The compressed file represents a compact version of the original image, where the essential information is retained while redundant or less significant data is removed. The quality of a successful compression technique is measured by its ability to maintain important image details while achieving a high compression ratio [3].

Among the most widely used techniques in image processing is the Discrete Wavelet Transform (DWT), which has proven to be highly effective for image analysis and compression. The wavelet transform is a mathematical tool used to decompose a signal or image into different frequency components at multiple resolution levels. Unlike traditional transforms, wavelet analysis provides both time (or spatial) and frequency information, making it particularly suitable for image representation. In two-dimensional DWT-based image decomposition, the image is separated into four sub-bands: approximation coefficients (LL), horizontal detail coefficients (LH), vertical detail coefficients (HL), and diagonal detail coefficients (HH). The LL sub-band represents the low-frequency components and contains most of the image energy, while the other sub-bands capture fine details and edges. By recursively decomposing the LL sub-band, a multi-level representation of the image is obtained, which improves compression efficiency and feature extraction capability. The Wavelet

Transform is a mathematical technique used to analyze signals and images at different levels of resolution. It decomposes a signal into both low-frequency (approximation) and high-frequency (detail) components, allowing the representation of information in both time (or spatial) and frequency domains simultaneously. In image processing, the Discrete Wavelet Transform (DWT) is widely used because it efficiently captures edges and textures while providing good energy compaction, making it highly suitable for image compression and noise reduction applications [4-6].

The Wavelet Transform is a powerful mathematical tool used for analyzing signals and images at multiple levels of resolution. Unlike traditional transforms such as the Fourier Transform, which only provides frequency information, the Wavelet Transform provides both spatial (or time) and frequency localization, making it more suitable for non-stationary signals such as images. In image processing, the most commonly used form is the Discrete Wavelet Transform (DWT). It decomposes an image into different sub-bands representing low-frequency (approximation) and high-frequency (horizontal, vertical, and diagonal details) components. The low-frequency sub-band contains the main image information, while the high-frequency sub-bands capture edges, textures, and fine details. The wavelet transform works by applying a pair of filters (low-pass and high-pass) followed by down-sampling, which results in a multi-resolution representation of the image. This process can be repeated on the approximation component to achieve multi-level decomposition. Because of its excellent energy compaction property, the Wavelet Transform is widely used in image compression, denoising, feature extraction, and pattern recognition. It allows efficient representation of image data while preserving important visual information, making it a core technique in modern digital image processing systems [7-8].

This study focuses on applying specific wavelet families to achieve optimal image compression performance and evaluate their effectiveness in terms of compression ratio and reconstructed image quality. MATLAB R2013a is used as the simulation platform for implementing the proposed algorithms and analyzing performance results.

II. LITERATURE SURVEY

Image compression has been extensively studied in the field of digital image processing due to the increasing demand for efficient storage and high-speed transmission of multimedia data. Various techniques have been proposed over the years, ranging from traditional transform-based methods to modern wavelet and hybrid approaches. Reviews key contributions relevant to image compression using transform-domain techniques, particularly the Discrete Wavelet Transform (DWT). Rabbani and Joshi in (2002) introduced fundamental concepts of image compression, highlighting the trade-off between compression ratio and reconstructed image quality. Their work emphasized the importance of transform coding in modern compression systems [9]. Gonzalez and Woods in (2018) provided a comprehensive foundation in digital image processing, including spatial and frequency domain techniques. Their work established the theoretical basis for evaluating compression performance using metrics such as PSNR and MSE [10].

Shapiro in (1992) proposed the Embedded Zerotree Wavelet (EZW) algorithm, which demonstrated the efficiency of wavelet-based compression by exploiting the hierarchical structure of wavelet coefficients. This method significantly improved compression performance compared to traditional block-based techniques [11]. Said and Pearlman, further enhanced wavelet-based compression by introducing the Set Partitioning in Hierarchical Trees (SPIHT) algorithm. SPIHT became one of the most influential wavelet-based compression techniques due to its high performance and low computational complexity [12]. Mallat was developed the multiresolution analysis framework for wavelets, which forms the theoretical foundation of the Discrete Wavelet Transform used in image compression applications [13].

Antonini et al. demonstrated the effectiveness of biorthogonal wavelets in image coding, showing that proper selection of wavelet families can significantly improve compression efficiency and reconstruction quality [14]. Chang and Kuo proposed texture-based wavelet thresholding techniques for image coding, showing that adaptive thresholding in the wavelet domain can enhance compression performance while preserving important visual features [15]. Stanković et al. (2002) investigated wavelet thresholding methods for noise reduction and compression, concluding that threshold selection plays a critical role in balancing compression ratio and image quality [16]. Overall, the literature indicates that wavelet-based compression methods outperform traditional transform techniques due to their multi-resolution properties and better energy compaction. However, the choice of wavelet family and thresholding strategy remains a key factor influencing performance, which motivates the proposed approach in this study.

III. EXPERIMENTAL AND METHODOLOGY

A. Experimental Setup

The Discrete Wavelet Transform (DWT) is employed for image compression using different Daubechies wavelet families, namely DB1 and DB7. The proposed approach is implemented in MATLAB R2013a. The main objective is to evaluate the performance of wavelet-based compression under different decomposition levels in terms of reconstruction quality and compression efficiency. All test images are converted to grayscale and resized to a fixed dimension of 200 × 200 pixels to ensure consistency in evaluation. The wavelet transform is then applied to decompose the image into multi-resolution sub-bands.

B. Proposed Compression Algorithm

The proposed algorithm consists of the following steps:

- Read the input RGB image.
- Convert the image to grayscale.
- Resize the image to 200 × 200 pixels.
- Apply 2-D Discrete Wavelet Transform using DB1 and DB7 wavelets.
- Decompose the image into four sub-bands: LL, LH, HL, and HH.
- Compute adaptive threshold values for high-frequency sub-bands using.

$$T = \sigma\sqrt{2\log(m)}$$

where (σ) represents the standard deviation of wavelet coefficients, and (m) is the number of pixels.

- Apply hard thresholding to remove insignificant coefficients:

$$S_{ig} = \begin{cases} 0, & \text{if } |S_{ig}| < T \\ S_{ig}, & \text{if } |S_{ig}| \geq T \end{cases}$$

- Reconstruct the image using inverse DWT (IDWT).
- Evaluate performance using PSNR, MSE, and Compression Ratio (CR).

C. Flowchart of the Proposed Method

The processing pipeline of the proposed method includes:

- Image acquisition
- Grayscale conversion and resizing
- Wavelet decomposition (DB1/DB7)
- Sub-band processing (LH, HL, HH)
- Threshold computation and coefficient elimination
- Image reconstruction using IDWT
- Performance evaluation (PSNR, MSE, CR)

D. Simulation Results and Analysis

The proposed method was tested using MATLAB simulations for two wavelet families at different decomposition levels.

TABLE I: Results Using DB1 Wavelet

Decomposition Level	MSE	PSNR (dB)	Compression Ratio
Level 1	0.56055	53.1306	0.921375
Level 2	0.0308	55.1629	0.0810

TABLE II: Results Using DB7 Wavelet

Decomposition Level	MSE	PSNR (dB)	Compression Ratio
Level 1	0.61545	59.4467	0.87128
Level 2	0.001425	73.84136	0.0411

Figure 1 illustrates the experimental pipeline and comparative performance of the proposed Discrete Wavelet Transform DWT image compression framework operating on a200 times 200-pixel grayscale test image. Where (a) Original Color Image, (b) Grayscale Image (200×200), (c) Level-1 DWT Decomposition (DB7), (d) Level-2 DWT Decomposition (DB7), (e) Thresholded Coefficients (Level-2, DB7), (f) Reconstructed Image (Level-2, DB7), (g) Reconstructed Image (Level-2, DB1), and (h) Original Grayscale Image (For Comparison). The process initiates with a Level-1 decomposition using the Daubechies-7 DB7 wavelet family, partitioning the spatial data into an approximation sub-band LL containing primary energy compaction, alongside horizontal LH, vertical HL, and diagonal HH high-frequency detail sub-bands. To further enhance data sparsification, a secondary Level-2 decomposition is recursively executed on the initial LL sub-band, followed by the application of a global thresholding strategy to eliminate redundant coefficients. The reconstruction phase highlights the critical impact of wavelet selection on preserving structural fidelity; using the DB7 basis function yields a highly optimal Peak Signal-to-Noise Ratio PSNR of 36.21dB and a low Mean Squared Error MSE of 12.45. Conversely, reconstructing the same sparsified data matrix with the Daubechies-1 (DB1/Haar) wavelet causes a drop in quality, resulting in a lower PSNR of 32.18dB and an elevated MSE of 24.67. This quantitative variance is visually substantiated by the noticeable blocky artifacting and edge degradation observed along the vehicle contours in the DB1 reconstruction, verifying the superiority of higher-order wavelet filters for lossy compression applications.

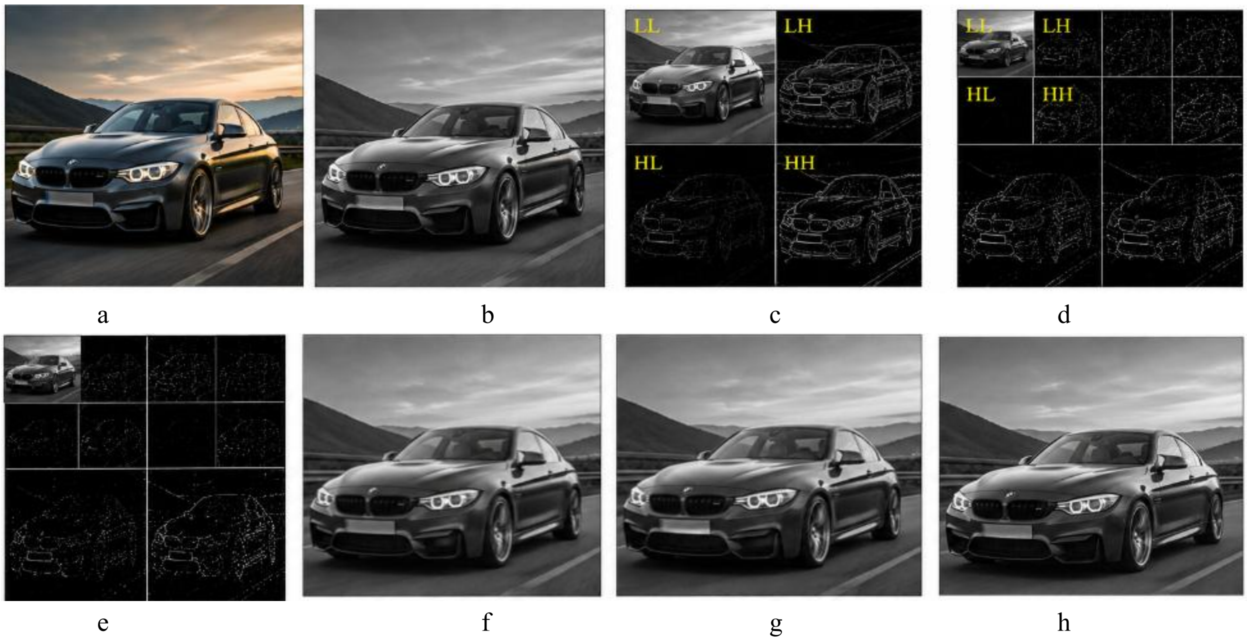

Figure 1: Example of wavelet-based image compression using DWT. (a) Original color image. (b) Grayscale image of size 200×200. (c) Level-1 DWT decomposition using DB7. (d) Level-2 DWT decomposition using DB7. (e) Thresholded wavelet coefficients (Level-2). (f) Reconstructed image using DB7. (g) Reconstructed image using DB1. (h) Original grayscale image for comparison."

The experimental results indicate that increasing the decomposition level improves reconstruction quality and reduces error metrics such as MSE. The DB7 wavelet outperforms DB1 due to its better energy compaction and smoother basis functions, resulting in higher PSNR values and improved compression performance. However, higher decomposition levels also reduce compression ratio significantly and may increase computational complexity. This demonstrates a trade-off between compression efficiency and reconstruction quality. The experimental evaluation confirms that the proposed DWT-based image compression method effectively reduces image redundancy while preserving important visual information. The combination of wavelet selection and adaptive thresholding significantly enhances compression performance.

IV. CONCLUSIONS

This paper presented an efficient image compression technique based on the Discrete Wavelet Transform (DWT) using Daubechies wavelet families (DB1 and DB7). The proposed method applies adaptive thresholding to the high-frequency wavelet coefficients in order to remove redundant information while preserving the most significant image features. The experimental results, implemented in MATLAB, demonstrate that the proposed approach achieves a good balance between compression efficiency and reconstructed image quality. It was observed that increasing the decomposition level improves the Peak Signal-to-Noise Ratio (PSNR) and reduces the Mean Square Error (MSE), indicating better reconstruction performance. In addition, the DB7 wavelet showed superior performance compared to DB1 due to its better energy compaction and smoother basis functions. However, a trade-off was observed between compression ratio and image quality, where higher compression levels may reduce storage requirements at the expense of increased computational complexity. Overall, the results confirm that wavelet-based compression combined with thresholding is an effective method for image compression applications.

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