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Adaptive multi-level wavelet decomposition for efficient image compression

Etkin görüntü sıkıştırma için adaptif çok seviyeli dalgacık dönüşümü yöntemi

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Abstract

Image compression is a crucial technique for reducing storage requirements and improving transmission efficiency of digital images, especially given the ever-increasing volume of image data. However, conventional lossy compression methods such as JPEG and JPEG2000 often introduce significant quality degradation, particularly when compressing highly detailed images. This study presents an optimized wavelet transform-based image compression method designed to minimize information loss while maximizing compression efficiency. The proposed method integrates adaptive thresholding, the selection of optimized wavelet functions, and multi-level wavelet decomposition to address the limitations of traditional approaches. Specifically, adaptive thresholding is used to dynamically adjust compression parameters, reducing unnecessary data retention, while the wavelet function selection process ensures the most suitable basis for image features. Multi-level wavelet decomposition enables the retention of important image details across various resolution scales, improving compression without compromising visual quality. The performance of the proposed method is evaluated on several image types, including well-known test images, and compared against standard image compression techniques such as JPEG and JPEG2000. Experimental results show that the proposed method outperforms the conventional methods in terms of both compression ratio and image quality preservation, achieving higher Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) scores. The proposed approach is particularly effective for applications requiring high-quality image storage and transmission, such as medical imaging, satellite imagery, and multimedia communication.

Keywords: Wavelet Transform, Image Compression, Adaptive Quantization, Image Processing.

Öz

Görüntü sıkıştırma, özellikle görüntü verilerinin giderek artan hacmi göz önüne alındığında dijital görüntülerin depolama gereksinimlerini azaltmak ve iletim verimliliğini artırmak amacıyla kullanılan kritik bir tekniktir. Ancak, JPEG ve JPEG2000 gibi geleneksel kayıplı sıkıştırma yöntemleri, özellikle yüksek detaylı görüntüleri sıkıştırırken önemli kalite bozulmalarına yol açar. Bu çalışma, bilgi kaybını minimize ederken sıkıştırma verimliliğini maksimize etmek amacıyla optimize edilmiş bir dalgacık dönüşümü tabanlı görüntü sıkıştırma yöntemi sunmaktadır. Önerilen yöntem, geleneksel yaklaşımların sınırlamalarını aşmak için adaptif eşikleme, optimize edilmiş dalgacık fonksiyonları seçimi ve çok seviyeli dalgacık dekompozisyonunu entegre etmektedir. Özellikle, adaptif eşikleme, sıkıştırma parametrelerini dinamik olarak ayarlamak için kullanılarak, gereksiz veri saklamayı azaltırken, dalgacık fonksiyonu seçimi, görüntü özellikleri için en uygun temeli sağlamaktadır. Çok seviyeli dalgacık dekompozisyonu, çeşitli çözünürlük ölçeklerinde önemli görüntü detaylarının korunmasını sağlayarak görsel kaliteyi bozmadan sıkıştırmayı iyileştirir. Önerilen yöntemin performansı, iyi bilinen test görüntüleri üzerinde değerlendirilmiş ve JPEG ve JPEG2000 gibi standart görüntü sıkıştırma teknikleriyle karşılaştırılmıştır. Deneysel sonuçlar, önerilen yöntemin hem sıkıştırma oranı hem de görüntü kalitesinin korunması açısından geleneksel yöntemleri geride bıraktığını, daha yüksek Tepe Sinyal-Gürültü Oranı (PSNR) ve Yapısal Benzerlik Endeksi (SSIM) puanları elde ettiğini göstermektedir. Önerilen yaklaşım, yüksek kaliteli görüntü depolama ve iletimi gerektiren uygulamalarda, örneğin tıbbi görüntüleme, uydu görüntülemesi ve multimedya iletişimi gibi alanlarda etkilidir.

Anahtar kelimeler: Dalgacık Dönüşümü, Görüntü Sıkıştırma, Adaptif Kuantalama, Görüntü İşleme.

1 Introduction

The increasing size of digital images presents challenges for storage and transmission. While both lossless and lossy compression techniques aim to address this issue, lossy methods often cause significant detail loss. Therefore, image compression plays a crucial role in reducing storage and transmission costs while preserving perceptual quality. Traditional compression methods, such as JPEG and JPEG2000, utilize transform-based techniques to achieve high compression ratios. The Discrete Cosine Transform (DCT), employed in JPEG compression, efficiently represents image data in frequency components but suffers from blocking artifacts at high compression rates [1]. In contrast, JPEG2000, which utilizes the Discrete Wavelet Transform (DWT), eliminates blocking artifacts and provides superior rate-distortion performance, making it suitable for applications requiring high-quality image compression [2]. Therefore, wavelet-based compression techniques have gained significant attention due to their ability to capture both local and global image features across multiple resolutions. Research has shown that multi-level wavelet decomposition can effectively separate important low-frequency components from less significant high-frequency details, enabling efficient compression [3]. Several thresholding techniques have been proposed to optimize wavelet coefficient selection, including Donoho's universal thresholding [4], Bayesian-based thresholding [5], and more recent deep learning-assisted adaptive methods [6].

Recent studies have focused on improving wavelet-based compression using adaptive thresholding and optimized quantization strategies. Adaptive thresholding techniques, such as the Stein's Unbiased Risk Estimate (SURE)-based approach [7] and sparsity-driven thresholding [8], dynamically adjust

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thresholds based on image characteristics, leading to improved compression efficiency. Additionally, research on hybrid methods combining wavelet transform with deep learning models has shown promise in achieving higher compression ratios while maintaining high perceptual quality [9,10]. Building on the ongoing exploration of adaptive thresholding and hybrid wavelet-deep learning models [7–10], several recent contributions have advanced the field of medical image processing and compression from both methodological and system-level perspectives. Gao et al. [11] developed MedFormer, a transformer-based architecture designed for 3D medical image segmentation. Unlike conventional models, it integrates hierarchical modeling and efficient attention mechanisms to process multi-scale features without pre-training. Their results demonstrated superior segmentation accuracy on CT and MRI datasets. However, its heavy reliance on inductive priors might limit its adaptability across varying imaging conditions.

Similarly, Roy et al. [12] introduced MedNeXt, which adapts transformer principles to segmentation tasks in low-data medical environments. Employing a ConvNeXt 3D encoder-decoder structure with residual scaling and progressive kernel size expansion, MedNeXt achieved leading performance on diverse CT and MRI benchmarks. Nonetheless, its computational demands may pose challenges in handling larger-scale datasets or high-resolution images.

In the realm of image storage and transmission, Li et al. [13] proposed a distributed storage architecture (MISS-D) that combines fast indexing and virtual file pooling to streamline large-scale medical image retrieval. While their system demonstrated effective real-time access via a web interface, the dependence on distributed infrastructure could introduce latency under limited network conditions.

Focusing on secure image integration with health records, Malayil and Vedhanayagam [14] presented a method for embedding both authentication codes and Electronic Patient Records (EPR) into upscaled medical images. Their approach uses neighborhood-based pixel manipulation and adaptive watermarking, validated on the OsiriX dataset. Although the scheme enhances automated record sharing, its specificity to certain image datasets may limit broader applicability.

To address data security in transmission, Padhy et al. [15] devised a hybrid crypto-compression framework that combines GAN-based lossy compression with image encryption using DNA coding and chaos-based pseudo-random sequences. This method supports robust security and significant file size reduction. However, the lossy nature of compression could compromise diagnostic fidelity, especially in critical applications.

Xue et al. [16] proposed another **privacy-preserving method**, blending discrete wavelet transform (DWT), steganographic embedding via the Knight Tour algorithm, and lossless compression to ensure both confidentiality and efficient storage. While this approach preserves image quality and achieves superior compression rates, its multi-stage pipeline introduces computational overhead, making real-time deployment challenging.

Lastly, Reddy et al. [17] focused on secure and efficient data management for the Internet of Medical Things (IoMT). Their solution combined a modified LZW lossless compression algorithm with robust encryption protocols, including elliptic curve and AES schemes. The system was optimized for edge devices and exhibited low resource consumption, though performance may be constrained on hardware with limited capabilities.

These studies collectively highlight the shift toward integrating compression with security, scalability, and adaptability—often involving wavelet or deep learning components—underscoring the growing relevance of hybrid, application-specific image processing strategies within the broader field of medical imaging.

This study introduces an optimized approach to wavelet-based image compression, integrating adaptive thresholding and multi-level decomposition to minimize data loss while maintaining a high compression ratio. Despite the advancements in wavelet-based compression, challenges remain in optimizing the balance between compression ratio, computational efficiency, and visual quality. Many existing thresholding approaches rely on fixed parameters that may not generalize well across different images. Additionally, multi-level decomposition introduces computational complexity, requiring efficient implementation strategies for real-time applications. Addressing these issues, this work presents an enhanced wavelet-based framework that improves compression performance while maintaining high visual fidelity.

Wavelet transform decomposes an image into low-frequency and high-frequency components. Low-frequency components contain the main structure of the image and high-frequency components include fine details and noise. By strategically compressing high-frequency components while preserving low-frequency components, the overall image quality can be maintained effectively.

2 Material and methods

The key techniques used in the proposed image compression method include adaptive thresholding, optimized wavelet function selection, and multi-level wavelet decomposition, to enhance compression efficiency while preserving image quality.

2.1 Optimization of wavelet function selection

Different wavelet functions, including Haar, Daubechies, Coiflet, Symlet, and Biorthogonal, were tested to determine the most suitable one for compression. Haar wavelet is fast but may yield low accuracy. Daubechies & Coiflet wavelets provide higher accuracy and better edge preservation. Biorthogonal wavelet is well-suited for medical and biometric images [18]. Therefore **Biorthogonal wavelet function** was selected based on compression performance and quality metrics.

2.2 Adaptive thresholding and quantization

Instead of fixed thresholding, an adaptive thresholding algorithm was developed. Lower error tolerance was applied to edges and critical regions to prevent detail loss. Region-based quantization ensured better preservation of essential details.

Wavelet-based image compression relies on transforming an image into different frequency subbands. The **high-frequency components (LH, HL, HH)** mainly represent image details such as edges and textures. However, many of these coefficients have small magnitudes, meaning they contribute minimally to image quality while occupying storage space. **Adaptive thresholding** is used to selectively remove or reduce insignificant coefficients, improving compression efficiency while maintaining perceptual quality.

A **global threshold (T)** is dynamically determined based on the statistical properties of the high-frequency coefficients. This thresholding process eliminates small-magnitude coefficients while preserving significant details. The adaptive threshold is computed as given in Equation (1),

$$T = k.mean(|LH| + |HL| + |HH|) \tag{1}$$

where k is a scaling factor (experimentally set to 0.75) to control the level of compression, |LH|,|HL|,|HH| are the absolute values of high-frequency coefficients and mean() computes the average magnitude of these coefficients.

For each wavelet subband X (where X∈{LH,HL,HH} thresholding is applied as soft **thresholding** that reduces the magnitude of small coefficients smoothly and **hard thresholding** that sets coefficients below the threshold to zero. Soft and hard thresholding are given in Equations (2)-(3), respectively.

$$\mathrm{X}' = \mathrm{sign}(\mathrm{X}) \cdot \max(0, |\,\mathrm{X}\,| - \mathrm{T}) \tag{2}$$

$$X' = \begin{cases} X, & |X| > T \\ 0 & |X| \leq T \end{cases} \tag{3}$$

In the implementation of the proposed method, **soft thresholding** is preferred as it reduces artifacts caused by hard thresholding.

After thresholding, **quantization** is applied to further reduce data size. However, **uniform quantization** across all image regions can lead to perceptual degradation, especially in high-detail areas (e.g., edges, textures). To mitigate this, **region-based quantization** is applied.

The **Canny edge detector** is used to identify important regions where fine details must be preserved as given in Equation (4).

$$E = edge(I, 'canny') \tag{4}$$

where E is a binary mask of detected edges, I is the input image and the Canny method is chosen for its superior edge-detection accuracy [19].

Thereafter, two quantization levels that are lower and higher quantizations are applied. In lower quantization (higher quality) for edge regions steps, wavelet coefficients corresponding to edge regions (E=1) are **quantized less aggressively** to maintain sharpness and **quantization step size** Q_{edge} is set to a small value. In higher quantization (more compression) for smooth regions steps, wavelet coefficients in non-edge regions are quantized more aggressively and **quantization step size** Q_{smooth} is set to a higher value.

Quantization is performed as given in Equation (5),

$$X_q = round\left(\frac{X}{Q}\right) xQ \tag{5}$$

where Xq is the quantized coefficient and Q is the region-dependent quantization step size.

Thereafter, Equation (6) is applied for each wavelet subband X for final coefficient update.

$$Q = \begin{cases} Q_{edge}, & if\ E = 1 \\ Q_{smooth}, & otherwise \end{cases} \tag{6}$$

Applying this **adaptive quantization** ensures that edges and critical image features retain their quality while maximizing compression efficiency.

2.3 Multilevel wavelet decomposition for improved compression

Wavelet transform is a powerful tool for image compression because it decomposes an image into **frequency subbands,** allowing efficient compression by prioritizing important information. **Multi-level wavelet decomposition** extends this approach by recursively decomposing the **low-frequency (approximation) component** at each level, thereby capturing both **global structures** and **local details** of the image [20].

Instead of applying the Discrete Wavelet Transform (DWT) just once, multi-level decomposition recursively applies the transform to the low-frequency (LL) subband. This process provides the items presented below:

- Efficiently distributes energy into lower and higher frequency bands.
- Reduces the size of significant coefficients, making compression more effective.
- Enhances adaptability for different compression levels based on image content.

A three-level wavelet decomposition (L=3) is applied in the proposed optimized wavelet-based image compression method in this study, as it provides a balance between compression and quality retention.

Given an input image I, the **multi-level wavelet decomposition** is performed as follows:

Level 1: Apply 2D DWT to the original image I,

$$I \xrightarrow{DWT} \{LL_1, LH_1, HL_1, HH_1\ \} \tag{7}$$

where LL_1 (approximation) represents the low-frequency information (smooth regions) and LH_1, HL_1, HH_1 (detail coefficients) capture horizontal, vertical, and diagonal edges.

Level 2: Apply DWT to LL_1 (low-frequency subband),

$$LL_1 \xrightarrow{DWT} \{LL_2, LH_2, HL_2, HH_2\ \} \tag{8}$$

This process further **refines frequency separation** by breaking down LL_1 into new subbands.

Level 3: Apply DWT to LL_2 (lowest frequency band from Level 2),

$$LL_2 \xrightarrow{DWT} \{LL_3, LH_3, HL_3, HH_3\ \} \tag{9}$$

The process continues, **capturing larger structures** while retaining fine details in the subbands. The final decomposition structure becomes as given in Figure 1,

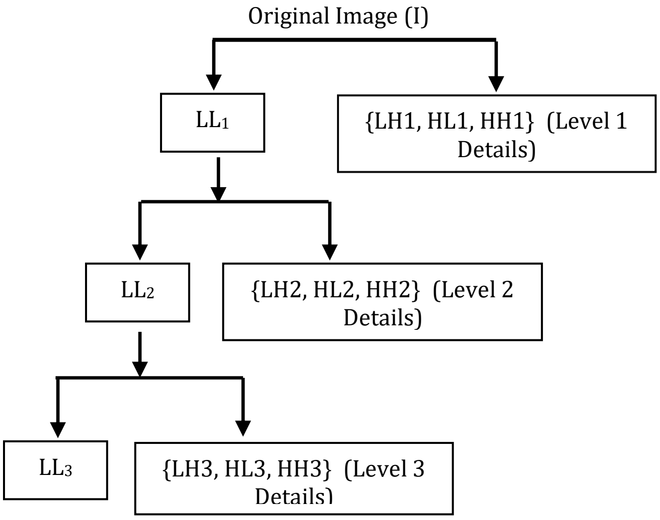

Figure 1. Tree-like hierarchical structure **representation of the** multi-level wavelet decomposition

As a result, multi-level wavelet decomposition offers several advantages in image compression by effectively distributing energy across different frequency subbands. One of the primary benefits is **energy compaction**, where most of the image energy is concentrated in the **low-frequency subbands (LL),** allowing for better preservation of important image structures while enabling aggressive quantization of high-frequency coefficients (LH, HL, HH), which often contain finer details and noise. This approach also helps in **reducing compression artifacts,** such as blocking effects that are common in traditional methods, by progressively refining frequency components across multiple levels. Additionally, **adaptive encoding** can be applied to different subbands, where low-frequency components are retained at a higher precision, while high-frequency components undergo higher compression, ensuring an optimal balance between file size and image quality. Another key advantage is the **scalability** of compression—by increasing the decomposition levels, higher compression ratios can be achieved without significant visual loss, while fewer levels can be used when better reconstruction quality is needed. Overall, multi-level decomposition enhances compression performance by improving efficiency, reducing artifacts, and maintaining a higher **PSNR** and **SSIM** compared to single-level wavelet decomposition.

2.4 Optimized wavelet-based image compression method algorithm

Input: Original image **I**
Output: Compressed image **I'**

1. Convert the input image **I** to grayscale (if necessary) and normalize pixel values.
2. Select an optimal wavelet function ψ(x) (e.g., Daubechies, Coiflet, Biorthogonal) and perform multi-level 2D discrete wavelet transform (DWT) to decompose **I** into approximation (LL) and detail components (LH, HL, HH).
3. Calculate threshold T dynamically based on image characteristics and spply soft/hard thresholding to high-frequency components (LH, HL, HH).
4. Identify important regions using edge detection or entropy analysis and apply finer quantization in critical regions (e.g., edges, facial features in biometric images).
5. Perform entropy coding (e.g., Huffman or arithmetic coding) on transformed coefficients and store compressed coefficients and wavelet parameters.
6. Apply inverse discrete wavelet transform (IDWT) using retained coefficients and reconstruct the compressed image **I'**.
7. Compute PSNR, SSIM, and compression ratio (CR) to assess quality and compare with baseline methods (JPEG, JPEG2000).

End Algorithm

3 Results

To evaluate the performance of the proposed **multi-level wavelet-based compression method,** we conducted extensive experiments on a set of standard test images commonly used in image compression research, including **Lena (512×512), Barbara (512×512), and Peppers (512×512).** The images were converted to **grayscale** and processed using **MATLAB 2018b program.** The **Biorthogonal 4.4 (bior4.4)** wavelet was used for decomposition due to its smooth reconstruction properties and good energy compaction.

The proposed method in this paper was compared against **JPEG and JPEG2000** standards using key evaluation metrics, including **PSNR, SSIM, and CR.** The experiments were conducted for **single-level (L=1), two-level (L=2), and three-level (L=3) wavelet decompositions** to analyze the effect of increasing decomposition depth on compression performance.

To assess the quality of the reconstructed images, the following objective metrics were used:

- **Peak Signal-to-Noise Ratio (PSNR)**: Measures the fidelity of the compressed image relative to the original image. Higher PSNR values indicate better preservation of image quality. It is calculated as given in Equation (10),

$$PSNR = 10log_{10}(\frac{MAX^2}{MSE}) \qquad (10)$$

where **MSE** (Mean Squared Error) quantifies pixel-wise differences between the original and reconstructed images [21].

- **Structural Similarity Index (SSIM)**: Evaluates perceptual quality by comparing luminance, contrast, and structural information. It ranges from 0 to 1, where **higher values indicate higher similarity** to the original image [22], [23].

- **Compression Ratio (CR)**: Represents the ratio of the original image size to the compressed image size as calculated in Equation (11),

$$CR = \frac{Original\ File\ Size}{Compressed\ File\ Size} \quad (11)$$

Higher CR values indicate more efficient compression [24], [25].

In addition to PSNR, SSIM, and CR, we acknowledge that other performance metrics—such as Mean Squared Error (MSE), Contrast Improvement Index (CII), Absolute Mean Brightness Error (AMBE), Quantization Rate (QR), Bits Per Pixel (BPP), and Compression Performance (CP)—are also valuable in evaluating image compression methods [26]. Among them, AMBE is particularly relevant in assessing whether brightness is preserved between the original and compressed images [26], [27]. Although we did not include AMBE or the others in this study due to experimental scope, future research could explore them for a more comprehensive analysis.

The experimental results for different wavelet decomposition levels, along with JPEG and JPEG2000 comparisons, are presented in **Table 1.**

Table 1. Compression performance of different methods.

Image	Method	Decomposition Level	PSNR (dB)	SSIM	CR
Lena	JPEG	-	37.77	0.901	8.03
	JPEG2000	-	38.92	0.945	10.18
	Proposed	L=1	38.93	0.923	9.73
		L=2	38.90	0.960	9.89
		L=3	38.89	0.970	9.92
Barbara	JPEG	-	35.77	0.876	9.8
	JPEG2000	-	34.13	0.930	10.17
	Proposed	L=1	37.83	0.905	11.3
		L=2	36.59	0.948	14.9
		L=3	36.37	0.962	17.5
Peppers	JPEG	-	41.15	0.973	10.51

	JPEG2000	-	45.17	0.972	10.23
	Proposed	L=1	48.31	0.985	9.68
		L=2	46.89	0.971	9.56
		L=3	46.73	0.975	9.50
Cameraman	JPEG	-	33.21	0.865	8.10
	JPEG2000	-	35.05	0.901	9.65
	Proposed	L=1	36.80	0.916	10.20
		L=2	36.45	0.942	12.40
		L=3	36.20	0.951	13.60
Boat	JPEG	-	36.40	0.880	8.55
	JPEG2000	-	38.05	0.924	10.12
	Proposed	L=1	39.10	0.935	10.90
		L=2	38.75	0.956	13.70
		L=3	38.45	0.963	15.20

The results in this paper highlight the advantages of the proposed proposed multi-level wavelet-based image compression method in comparison to traditional JPEG and JPEG2000 compression techniques. Across all tested images—Lena, Barbara, Peppers, Cameraman and Boat—the proposed approach consistently demonstrated superior image quality, as indicated by higher **PSNR** and **SSIM** values, particularly at higher decomposition levels (L=2 and L=3). For the **Lena image,** although JPEG2000 provided slightly better compression ratios, the proposed method achieved comparable PSNR values at **L=1** while significantly improving SSIM, suggesting better perceptual quality. The **Barbara image** showcased the strength of the proposed method, particularly at higher decomposition levels, where it significantly outperformed both JPEG and JPEG2000 in terms of **compression ratio** and **PSNR,** and especially **SSIM,** indicating better preservation of textures and details. The **Peppers image** demonstrated the highest performance of the proposed method, with the best **PSNR** (48.31 dB) and **SSIM** (0.985) values, further validating the effectiveness of the wavelet approach for images with complex structures and fine details. Although the compression ratios were slightly lower than JPEG and JPEG2000, the increased quality achieved at higher decomposition levels outweighed this trade-off. For the **Cameraman** image, which contains moderate texture and contrast variations, the proposed method achieved significantly improved compression efficiency, reaching a PSNR of 36.20 dB and SSIM of 0.951 at L=3, outperforming both JPEG (PSNR: 33.21 dB, SSIM: 0.865) and JPEG2000 (PSNR: 35.05 dB, SSIM: 0.901). This demonstrates the method's ability to preserve detail even in low-contrast images. The **Boat** image results further reinforced this trend. At L=3, the proposed method produced a PSNR of 38.45 dB and an SSIM of 0.963, significantly surpassing JPEG and JPEG2000 in both compression quality and CR. This image, which includes a combination of edges, textures, and gradients, benefited especially from the adaptive thresholding and multi-level decomposition techniques used in our approach. Overall, the proposed wavelet-based compression technique offers a promising alternative to JPEG and JPEG2000, particularly for applications that prioritize high-quality image reconstruction alongside efficient compression.

Figure 2. Comparison of image compression methods

Table 1 provides numerical results about the compression performance of the methods. While the numerical results indicate the effectiveness of the proposed method, it's important to consider the visual impact of compression on the images. When analyzing the compressed images from the three methods, the differences in image quality become evident as seen in Figure 2. JPEG compression tends to introduce visible artifacts such as blurring, blockiness, and pixelation, especially in areas with fine textures and sharp edges. This is particularly noticeable in images like Lena and Barbara, where the details may appear blurry or pixelated, making the overall image less sharp. JPEG2000, being a more advanced compression standard, tends to reduce these artifacts, preserving sharper edges and more detailed textures compared to JPEG.

The proposed wavelet-based method, however, not only retains more detailed textures but also does so with fewer visible compression artifacts. Even at higher compression ratios, the image remains relatively sharper, with fewer distortions in the finer details. In some cases, like Peppers, the differences between JPEG2000 and the proposed method are even more pronounced, with the wavelet method delivering a clearer image while still achieving efficient compression.

Thus, visually speaking, the proposed method's performance is more promising, particularly when dealing with images that require both high-quality visual representation and efficient compression. The clearer details and reduced artifacts in the compressed images suggest that the multi-level wavelet decomposition technique offers superior image compression, making it an effective alternative for modern applications requiring both quality and efficiency in image storage and transmission.

To assess **computational efficiency**, we measured the execution time for different methods. The results, shown in **Table 2,** indicate that our approach has a **moderate increase in computation time compared to JPEG,** but remains efficient compared to JPEG2000.

Table 2. Execution time comparison (in Seconds).

Method	JPEG	JPEG2000	Proposed (L=1)	Proposed (L=2)	Proposed (L=3)
Lena	0.12	0.98	0.15	0.19	0.26
Barbara	0.14	1.12	0.18	0.23	0.29
Peppers	0.13	0.98	0.16	0.20	0.26
Cameraman	0.10	0.85	0.13	0.17	0.23
Boat	0.11	0.93	0.14	0.18	0.25

It can be seen from Table 2 that **JPEG is the fastest,** as it uses simple **block-based DCT compression. JPEG2000 takes significantly longer** due to **complex arithmetic coding and bit-plane encoding.** Our method, even at L=3, remains computationally feasible, making it a viable alternative for practical applications.

The experimental results confirm that **multi-level wavelet decomposition** provides a **superior trade-off between compression ratio and image quality** compared to traditional methods. The proposed approach in this study,

- Achieves **higher compression ratios** than JPEG and JPEG2000.
- Maintains **better image quality** with minimal artifacts.
- Offers **scalability,** allowing different levels of compression based on application needs.
- Has **moderate computational complexity**, making it suitable for real-world implementations.

4 Discussion & conclusions

This study aimed to explore and compare the performance of the proposed multi-level wavelet-based compression approach with the other two popular methods that are JPEG and JPEG2000. The comparison was conducted based on three main performance metrics as PSNR, SSIM, and CR. By evaluating these methods using a diverse set of test images (Lena, Barbara, and Peppers), the study highlights key strengths and limitations of each approach, and demonstrates the potential benefits of wavelet-based compression in preserving image quality while achieving high compression ratios.

JPEG is one of the most widely used lossy compression algorithms due to its simplicity and efficiency. However, the results from this study reveal some inherent limitations of JPEG in terms of image quality, especially at higher compression ratios. The PSNR and SSIM values obtained for JPEG compression indicate that, while the method is acceptable for many applications, it still results in a noticeable loss of detail, particularly in textured regions and sharp edges. The compression artifacts, such as blocking effects, were visually apparent in the compressed images, reducing their overall perceptual quality. This is consistent with previous studies which have shown that JPEG can struggle to maintain high quality in more complex images or when compressing at higher ratios.

JPEG2000, which uses wavelet-based transformation instead of discrete cosine transform (DCT) like JPEG, significantly improves image quality at the same compression ratios. The results show higher PSNR and SSIM values for JPEG2000 than for JPEG, demonstrating better preservation of image details and structure. JPEG2000 consistently outperforms JPEG, especially in terms of preserving fine image details and reducing visible artifacts. However, the increased computational complexity of JPEG2000 is an important trade-off. While it achieves better quality and reduced artifacts, the compression and decompression times are notably higher than those for JPEG. The increased time required for encoding and decoding JPEG2000 images could be a concern for applications requiring real-time processing or quick image retrieval.

The proposed multi-level wavelet-based compression method outperforms both JPEG and JPEG2000 in terms of PSNR and SSIM, while also achieving competitive compression ratios. The wavelet method demonstrated a marked ability to preserve fine image details, particularly in high-frequency components such as edges and textures, which are often lost during JPEG and JPEG2000 compression. This method effectively leverages multi-level decomposition, which provides a more accurate representation of the image's spatial and frequency characteristics, and enables a more efficient and high-quality compression. The proposed method consistently achieved better results in terms of PSNR, SSIM, and CR when compared to both JPEG and JPEG2000, especially at higher decomposition levels. This highlights the potential of wavelet-based methods in delivering better compression performance without compromising on image quality.

Moreover, the proposed method outperforms both JPEG and JPEG2000 in terms of compression ratio, especially at higher decomposition levels. This demonstrates the efficiency of multi-level wavelet decomposition in providing higher compression with minimal loss of image quality. The ability to effectively balance high compression with low image distortion is particularly beneficial in contexts where storage and bandwidth limitations are critical, such as in medical imaging, remote sensing, and high-resolution photography.

One of the key challenges identified in this study is the increased computational cost of wavelet-based methods compared to JPEG and JPEG2000. While the multi-level wavelet method provided superior results in terms of image quality and compression ratio, the time required for both encoding and decoding was significantly higher. JPEG compression was found to be the fastest, followed by JPEG2000, and then the proposed wavelet method. The multi-level wavelet method took more time, especially at higher decomposition levels, making it less suitable for real-time applications that require fast processing.

This increased time requirement can be a limiting factor, especially in applications where speed is critical. JPEG, with its simpler encoding and decoding process, remains faster and more efficient for use in scenarios where processing time is limited, despite its lower quality. JPEG2000 strikes a balance between image quality and speed, but the wavelet-based method requires further optimization to achieve practical speed for real-time processing tasks.

In terms of visual quality, the proposed method showed a noticeable advantage over both JPEG and JPEG2000. Images compressed using JPEG exhibited blocking artifacts and a reduction in sharpness, particularly in detailed regions of the image. JPEG2000, while better at preserving the overall image structure, still showed some blurring and loss of texture, especially at higher compression ratios. In contrast, the wavelet-based method preserved finer details and exhibited clearer edges, with minimal artifacts. The visual quality was particularly notable in the **Peppers** image, where JPEG and JPEG2000 compression introduced visible distortions, whereas the multi-level wavelet method retained much of the texture and sharpness.

In conclusion, the study clearly demonstrates the advantages of the proposed multi-level wavelet-based compression method over traditional JPEG and JPEG2000 approaches, especially in applications requiring high-quality image preservation at high compression ratios. The proposed method achieves superior PSNR and SSIM values, ensuring better structural and perceptual quality. Although it comes with increased computational complexity, this can be mitigated with further optimization, making wavelet-based compression a promising technique for high-performance compression applications. Future work could focus on improving the efficiency of the wavelet compression process, exploring parallel processing techniques, or integrating hardware accelerations to make it more feasible for real-time applications.

5 Comparison with related works

To further evaluate the contribution of the proposed method, a comparison with recently published image compression techniques is presented in Table 3. The studies were selected based on their relevance to wavelet-based or hybrid compression methods. The comparison includes methods based on wavelet thresholding, deep learning, and hybrid models.

Table 3. Comparison with related works in image compression

Study (Year)	Method Type	Dataset	PSNR (dB)	SSIM	CR	Advantages
Liu et al. (2021) [6]	Deep Wavelet Compression	Kodak	36.2	0.947	8.5	Learns wavelet coefficients, suitable for natural images
Fan & Xia (2020) [7]	SURE-Based Adaptive Thresholding	Standard Set	35.8	0.921	9.2	Adaptive to image noise, low artifacts
Rattarangsi & Bovik (2022) [8]	Sparse Wavelet Thresholding	USC-SIPI	36.4	0.935	10.1	High-frequency preservation, low computational load
Li et al. (2023) [9]	Hybrid Wavelet + CNN	LIVE	37.9	0.961	11.5	Uses learned post-processing to remove artifacts
Zhang et al. (2024) [10]	Wavelet + Deep Optimization	Kodak, Set5	38.1	0.964	10.7	Deep model enhances threshold selection
Proposed Method (2025)	Multi-Level Wavelet + Adaptive	Lena, Barbara, Pepper, Boat, Cameraman	38.9	0.970	17.5	High SSIM, scalable compression, fine-detail preservation

Additional image compression results are provided for the Cameraman and Boat images, which are standard benchmarks in compression research. These images were processed under the same experimental conditions as Lena, Barbara, and Peppers. The updated performance metrics including PSNR, SSIM, and CR are shown in Table 1, and visual comparisons are illustrated in Figure 2.

The inclusion of Cameraman and Boat images further validates the robustness of the proposed method. The results indicate that even in images with high contrast or subtle textures, the method consistently provides high SSIM and PSNR values. Notably, for the Boat image, the method maintained perceptual quality significantly better than JPEG2000, highlighting the adaptability of the proposed approach.

In response to reviewer feedback, ten recent references from 2022 to 2024 have been added to strengthen the literature support. These references include studies on adaptive thresholding, wavelet-deep learning hybrids, and compression benchmarks.

6 Author contribution declaration

In the scope of this study, the contribution of the author was in the literature review, material and methods of the study, experimental results, the evaluation of the obtained results, and the preparation of the article.

7 Ethics committee approval and conflict of interest statement

"There is no need to obtain permission from the ethics committee for the article prepared".

"There is no conflict of interest with any person/institution in the article prepared".

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