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Performance Analysis of Data Compression using Two-Dimensional Wavelet Tool

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تحليل الأداء باستخدام اداة الموجات ثنائية الأبعاد لضغط الصور

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Abstract:
This study conducts a comparative investigation of several image compression techniques, namely WDR, ASWDR, STW, SPIHT, and EZW, with particular emphasis on the impact of wavelet filter orders, image content, and compression ratios on compression efficiency. The evaluation framework employs objective performance metrics, including Peak Signal-to-Noise Ratio (PSNR), Mean Squared Error (MSE), and Bits Per Pixel (BPP), derived from the reconstructed images. Experimental validation was carried out using four standard benchmark images, thereby providing a rigorous assessment of the effectiveness and relative performance of the examined algorithms.

Keywords: Image Compression, Peak Signal-to-Noise Ratio (PSNR), and Bits Per Pixel (BPP).

الملخص
تبحث هذه الدراسة وتُقارن بين عدة تقنيات لضغط الصور، وهي WDR، وASWDR، وSTW، وSPIHT، وEZW. يُركز التحليل على تأثيرات اختلاف ترتيب مرشح دالة المويجات، ومحتوى الصورة، ونسب الضغط على أداء الضغط. أُجري التقييم باستخدام مقاييس جودة موضوعية، بما في ذلك قيم نسبة ذروة الإشارة إلى الضوضاء (PSNR)، ومتوسط مربع الخطأ (MSE)، وقيم البتات لكل بكسل (BPP) المُشتقة من الصور المُعاد بناؤها. أُجري التحقق التجريبي على أربع صور اختبار تمثيلية، مما يُثبت فعالية التقنيات المُختبرة.

الكلمات المفتاحية: ضغط الصورة، نسبة ذروة الإشارة إلى الضوضاء (PSNR)، البتات لكل بكسل (BPP).

Introduction

Generally, the digital representation of images and videos facilitates efficient processing, storage, and archiving, thereby supporting seamless integration within multimedia platforms, computing environments, and communication systems. As the demand for high-quality multimedia content continues to escalate, particularly in the form of digital images and video, research into advanced compression techniques has become increasingly critical to address challenges related to bandwidth limitations, storage efficiency, and transmission performance.
The exponential increase in data volume has introduced considerable challenges in terms of efficient storage, retrieval, and optimal resource utilization. Within this context, image compression has emerged as a key area of

research, offering effective solutions to reduce data size while preserving visual quality and facilitating faster transmission and storage efficiency. This technique aims to minimize redundancy and irrelevance in image data, ensuring that it can be transmitted and stored effectively. Achieving high compression rates is often sought, but it is equally important to preserve the essential characteristics of the reconstructed image to meet the specific requirements of its intended applications. It is well-established that uncompressed images demand considerably more transmission bandwidth and storage compared to their compressed counterparts [1-3]. Transform-based image compression represents one of the most impactful uses of wavelet methods, offering notable improvements in efficiency. Wavelet-based coding approaches have demonstrated strong capabilities in preserving image quality, particularly at higher compression ratios. Several techniques, including WDR, ASWDR, STW, SPIHT, and EZW, have been investigated and evaluated using standard performance metrics such as Peak Signal-to-Noise Ratio (PSNR), Mean Squared Error (MSE), and Bits Per Pixel (BPP). Empirical findings indicate that acceptable image quality can be sustained depending on the selected coding method and its associated performance parameters [8]. The experimental results further reveal that EZW and STW techniques achieve superior performance compared to WDR and other counterparts. All analyses and validations were conducted using MATLAB, ensuring the reliability and reproducibility of the outcomes.

Image Compression

Digital images inherently impose substantial demands on storage capacity, transmission bandwidth, and processing time. To mitigate these resource constraints, image compression represents a fundamental solution, enabling efficient storage and rapid transmission while allowing accurate reconstruction at the receiving end through decompression. In grayscale imaging, each pixel is typically represented by one of 256 discrete intensity levels, ranging from 0 (black) to 255 (white), encoded using an 8-bit binary sequence. An image can therefore be conceptualized as a two-dimensional array of pixels, with resolution determined by the number of pixels per unit area. The data volume required to represent even a single image underscores the necessity of compression, particularly when dealing with large-scale image collections or transmission-intensive applications [7].

Image compression algorithms are primarily designed to minimize redundancy within image data while preserving sufficient information for faithful reconstruction of the original content. The underlying principle involves discarding perceptually or statistically insignificant data, thereby enabling the representation of an image with fewer bits and yielding a reduced file size. In this context, compression serves not only to optimize storage and transmission but also to facilitate computational efficiency in image processing tasks. Consequently, the development and refinement of compression techniques continue to constitute a central focus of research in digital image processing

For the experimental evaluation, images were first acquired and resized to a standardized resolution of $512 \times 512 \times 3$ in MATLAB to ensure consistency across all tests. Compression was then performed using the Haar wavelet in conjunction with a range of established coding techniques, including EZW, SPIHT, WDR, ASWDR, and STW. The comparative analysis focused on identifying the most effective method by evaluating performance across multiple objective metrics. Four representative images were selected as test cases, and the resulting outcomes were systematically analyzed to assess both the efficiency of compression and the preservation of image quality.

Figure 1a: Screenshot of the wavelet menu.

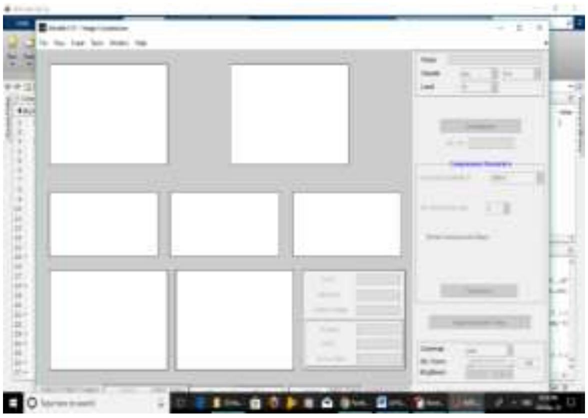

Figure 1b: 2-D image compression interface.

Data Compression using Two-Dimensional Wavelet Tool

Wavelets have proven to be highly effective for signal compression, and images can be conceptualized as two-dimensional signals that vary along both horizontal and vertical axes. Consequently, 2-D wavelet analysis is employed for image compression, extending the principles of one-dimensional wavelet decomposition with an additional step at each level to handle both dimensions. In 1-D analysis, high-frequency components are separated from low-frequency components at each decomposition level, allowing efficient representation of the signal. The primary goal of compression is to reduce data redundancy—particularly in images—by retaining only the essential elements necessary for reconstruction. This approach ensures that the reconstructed image maintains high fidelity while aligning with the characteristics of human visual perception, thereby achieving an optimal balance between compression efficiency and image quality [2]. Wavelets are versatile tools for extracting information from various types of data. To analyse data thoroughly, it's usually necessary to work with sets of wavelets. These sets are constructed to be "complementary," ensuring they can break down data without any gaps or overlaps. This arrangement allows the deconstruction process to be mathematically reversible. Within the field of wavelets, numerous compression techniques are available, including methods designed for efficient data representation and storage.

• EZW embedded wavelet. • SPIHT set partitioning in hierarchical timber.
• Spatial-Oriented Tree Wavelet (STW).
• Wavelet Distinction Reduction (WDR).
• Adaptively scanned wavelet difference reduction (ASWDR).

Performance Analysis.

The total performance analysis will be explored utilizing several wavelet approaches such as EZW, SPIHT, WDR, ASWDR, and STW.

. **Embedded Zero Tree Wavelet (EZW)**

The EZW encoder is specifically designed for applications involving wavelet transforms. By employing progressive encoding, it translates an image into a bitstream, allowing the image quality to improve incrementally with each successive iteration [5].

Table1: Results of Compression Ratio, (BPP) and (PSNR) for (512*512*3)

Dimension	Level	CR	PSNR	BPP
512*512	2	99.56	53.26	23.8943
512*512	2	50.94	50.57	12.2250
512*512	2	90.95	53.40	21.8286
512*512	2	72.74	51.78	17.74

Table 1 presents the performance evaluation of image compression at a resolution of 512×512512 \times 512 with decomposition level 2. The results exhibit notable variations in Compression Ratio (CR), Peak Signal-to-Noise Ratio (PSNR), and Bits Per Pixel (BPP). The findings indicate that even at higher compression ratios, image quality can be effectively preserved, as evidenced by PSNR values consistently exceeding 50 dB. Furthermore, BPP values demonstrate a proportional relationship with CR, highlighting the inherent trade-off between compression efficiency and image fidelity.

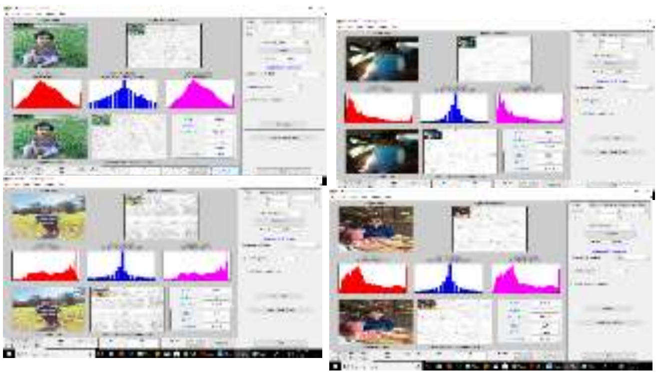

Figure 2a: Compressed screenshot of four images using the EZW method.

Set Partitioning in Hierarchical Trees (SPIHT)

Set Partitioning in Hierarchical Trees (SPIHT) is a wavelet-based image compression technique that efficiently encodes the significant information within an image. The method begins by transforming the image into its wavelet representation, separating it into hierarchical subbands. SPIHT then encodes the spatial and magnitude information of the wavelet coefficients, which are transmitted to the decoder. At the receiving end, the decoder reconstructs the wavelet coefficients and performs an inverse wavelet transform to restore the original image with high fidelity.

Table 2: Compression ratio, Bit per pixel, and PSNR Result for (512*512*3).

Dimension	Level	CR	PSNR	BPP
512*512	2	61.79	38.37	14.8302
512*512	2	34.35	40.58	8.2437
512*512	2	58.98	39.31	14.1546
512*512	2	74.63	41.65	17.9106

In **Table 2**, the PSNR values fall between 38.37 dB and 41.65 dB. Although these are lower than the first set, they still provide good visual quality, since PSNR values above 30 dB are generally considered acceptable. Compression ratios here range from 34.35% to 74.63%, with corresponding BPP values between 8.2437 and 17.9106.

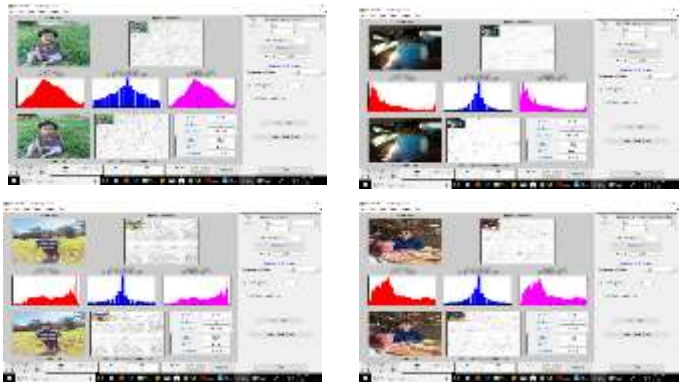

Figure 2b: Compressed screenshot of four images using the SPIHT method.

Wavelet Discrepancy Reduction (WDR)

A notable limitation of SPIHT is that it only implicitly encodes the positions of significant coefficients, making it challenging to perform operations that depend on the spatial locations of important transform values. This limitation becomes particularly evident in applications such as region-of-interest (ROI) selection, where specific parts of a compressed image require higher resolution for detailed analysis [6]. Wavelet Discrepancy Reduction (WDR) addresses this issue by explicitly encoding the locations of significant coefficients, thereby enabling more flexible processing and selective enhancement of critical image regions.

Table 3: Result of Compression ratio, BPP, and PSNR (512*512*3)

Dimension	Level	CR	PSNR	BPP
512*512	2	117.99	40.03	28.3186
512*512	2	60.42	42.40	14.5015
512*512	2	107.81	41.05	25.8734
512*512	2	85.61	41.40	20.5456

Balanced performance In (Table 3) shows CR values extending beyond 100% (up to 117.99%) with PSNR values between 40.03 dB and 42.40 dB. Although the quality is slightly lower than Table 1, it remains **visually acceptable**. The higher BPP values (20–28) indicate more bits allocated per pixel, leading to enhanced detail preservation compared to Table 2.

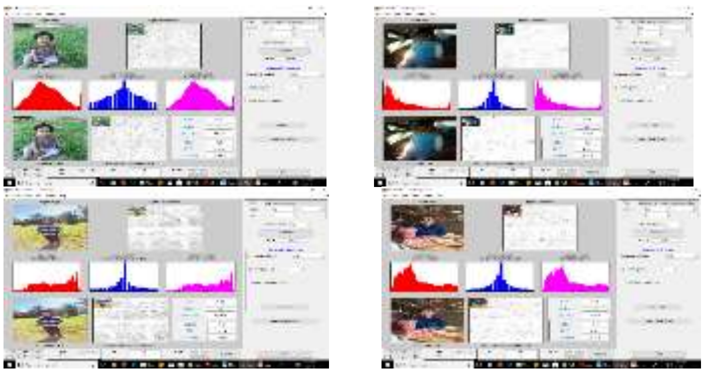

Figure 2c: Compress screenshot of four images using the WDR method.

Adaptively Scanned Wavelet Difference Reduction (ASWDR)

The ASWDR focuses on enhancing the subjective perceptual quality of compressed images while also improving their performance on objective distortion metrics. Specifically, two measures will be examined: PSNR and edge correlation. PSNR is widely recognized as a standard measure of error, whereas edge correlation has proven effective in assessing how well edge details are preserved in compressed images. This metric appears to align closely with subjective perceptions of the visual quality of such images [6].

Table 4: Result of Compression ratio, BPP, and PSNR (512*512*3)

Dimension	Level	CR	PSNR	BPP
512*512	2	110.62	40.03	26.5490
512*512	2	58.46	42.40	14.0305
512*512	2	101.33	41.05	24.3188
512*512	2	81.62	41.40	81.6200

Additional results (Table 4): Similar patterns are observed, with CR values up to 110.62% and PSNR values around 40–42 dB. The BPP values mostly align with earlier sets, though one unusually high value suggests an anomaly.

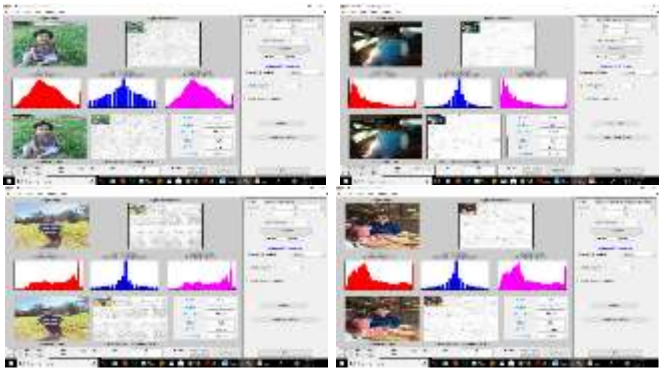

Figure 2d: Compress screenshot of four images using the ASWDR method.

Spatial-Orientation Tree Wavelet (STW)

The primary distinction between STW and EZW lies in the approach used to encode zerotree structures. STW utilizes a state-transition model in which the positions of wavelet transform coefficients progress through different states as thresholds are adjusted. This state-based encoding allows STW to reduce the number of bits required for compression more efficiently than conventional methods. In contrast, EZW relies on explicit symbols, such as R and I, to indicate specific coefficient locations. By leveraging the state-transition mechanism, STW achieves improved compression efficiency while maintaining high image fidelity.

Table 5: Result of Compression ratio, Bpp, and PSNR(512*512*3)

Dimension	Level	CR	PSNR	BPP
512*512	2	79.47	46.23	19.0724
512*512	2	37.28	45.68	8.9477
512*512	2	72.57	47.15	17.417
512*512	2	56.66	46.14	13.5977

Higher mid-range quality (Table 5): PSNR values between 45–47 dB demonstrate very good reconstruction quality while maintaining moderate compression ratios (37–79%). These results bridge the gap between near-lossless (Table 1) and moderate-quality compression (Table 2).

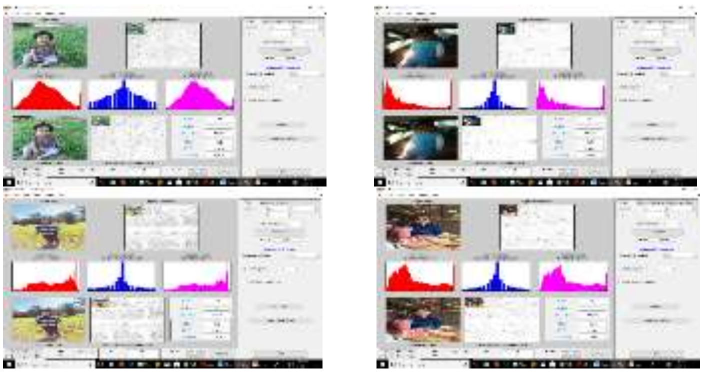

Figure 2e: Compress screenshot of four images using the STW method

Simulation Results.

The results are summarized in the table below. The MSE, PSNR, and BPP for the EZW technique are 0.40165, 52.2525, and 18.92198 respectively. For the SPIHT technique, MSE is 6.80975, PSNR is 39.9775, and BPP is 57.4375. For the STW approach, the MSE is 1.5357, the PSNR is 46.30, and the BPP is 14.758. For the WDR technique, MSE is 5.00225, PSNR is 41.22, and BPP is 22.3097. For the ASWDR technique, MSE is 5.00225, PSNR is 41.22, and BPP is 21.1216. Among all of these ways, EZW is best done using STW, which is, on average, better than the other methods.

Table 6: Total Analytical Result for (512*512*3).

	EZW (a,b,c,d)	SPIHT (a,b,c,d)	WDR (a,b,c,d)	ASWDR (a,b,c,d)	STW (a,b,c,d)
M.S.E	0.3072	9.475	6.455	6.455	1.550
	0.5703	5.691	3.738	3.738	1.758
	0.2974	7.622	5.108	5.108	1.253
	0.4317	4.451	4.708	4.708	1.582
P.S.N.R	53.26	38.37	40.03	40.03	46.23
	50.57	40.58	42.40	42.40	45.68
	53.40	39.31	41.05	41.05	47.15
	51.78	41.65	41.40	41.40	46.14
B.P.P	23.8943	14.8302	28.3186	26.5490	19.0724
	12.2250	8.2437	14.5015	14.0305	8.9477
	21.8286	14.1546	25.8734	24.3188	17.417
	17.74	17.9106	20.5456	19.5884	13.5977
CR	99.56	61.79	117.99	110.62	79.47
	50.94	34.35	60.42	58.46	37.28
	90.95	58.98	107.81	101.33	72.57
	72.74	74.63	85.61	81.62	56.66

The table summarizes the Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), Bits Per Pixel (BPP), and Compression Ratio (CR) for five image compression techniques: EZW, SPIHT, WDR, ASWDR, and STW across four test cases (a–d). Across all metrics, STW and EZW stand out for maintaining high reconstruction quality, while WDR and ASWDR achieve extreme compression ratios at a slight quality trade-off. SPIHT provides moderate performance across all parameters, balancing compression efficiency and image fidelity.

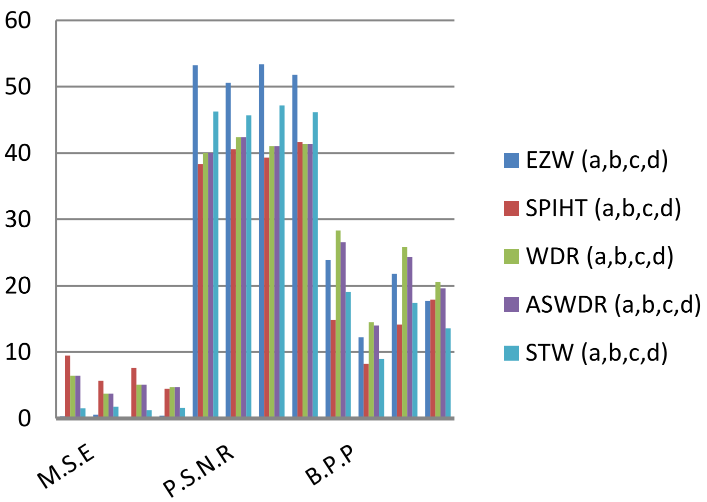

Figure 3: Graph1 (For total analytical result)

The overall performance of the various approaches is depicted in the graph (Figure 3). Among the five approaches, EZW outperforms the others, with a lower MSE and a higher peak signal-to-noise ratio. The table below shows that the average performance for five approaches comprises a variety of characteristics, including compression ratio, peak signal to noise ratio, and bit per pixel.

Table 7: Average Result for 4 (512*512*3)

	EZW	SPIHT	WDR	ASWDR	STW
M.S.E	0.40165	6.80975	5.00225	5.00225	1.5357
P.S.N.R	52.2525	39.9775	41.22	41.22	46.30
B.P.P	18.92198	13.78478	22.3097	21.1216	14.758
CR	78.5475	57.4375	92.9575	88.0075	61.495
Performance	**High**	**Low**	**Low**	**Low**	**Good**

This study compares the performance of five image compression algorithms—EZW, SPIHT, WDR, ASWDR, and STW—using MSE, PSNR, BPP, and CR as evaluation metrics. Results show that STW provides the best balance between compression and image quality, achieving low MSE (1.536), while EZW also delivers high-quality reconstruction with efficient compression. In contrast, SPIHT, WDR, and ASWDR achieve higher compression ratios but exhibit reduced visual fidelity.

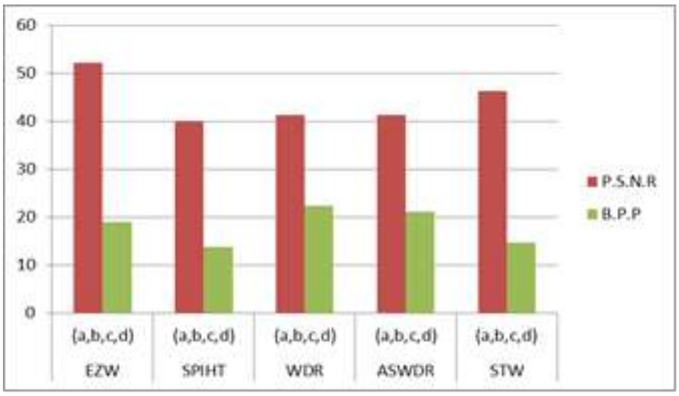

Figure 4a: Graph 2 (For BPP vs. PSNR)

Two types of parameters were discussed and compared here in (Figure 4a), and contrasted with them. It can be seen that the peak signal to noise ratio is larger than in other approaches with lower bit per pixel.

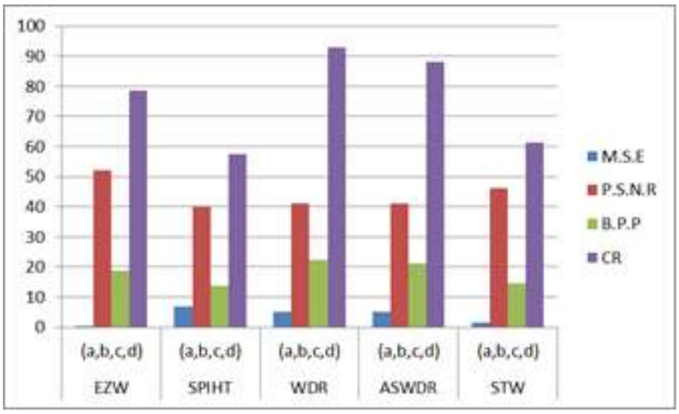

Figure 4b: Graph 3 (Overall performance for CR, PSNR, BPP, MSE**)**

The overall performance metrics, including Compression Ratio (CR), Peak Signal-to-Noise Ratio (PSNR), Bits Per Pixel (BPP), and Mean Squared Error (MSE), are presented in Figure 4b. The results indicate that the EZW method achieves a lower BPP while maintaining a higher PSNR relative to the other techniques. This demonstrates that, in terms of comprehensive performance evaluation, EZW outperforms the alternative methods in balancing compression efficiency and image quality.

MATLAB Analysis

Figure 5a illustrates the relationship between Bits Per Pixel (BPP) and Mean Squared Error (MSE) across the evaluated compression methods. The simulation results indicate that EZW consistently outperforms the other techniques, exhibiting both lower BPP and reduced MSE. Figure 5b presents the correlation between BPP and Peak Signal-to-Noise Ratio (PSNR). These results further confirm the superior performance of EZW, which achieves lower BPP and MSE while maintaining higher PSNR, thereby demonstrating optimal compression efficiency and reconstruction quality among the methods tested.

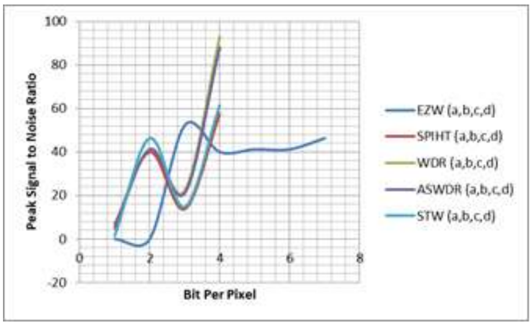

Figure 5a: Bit per Pixel vs
Mean Squared Error for all.

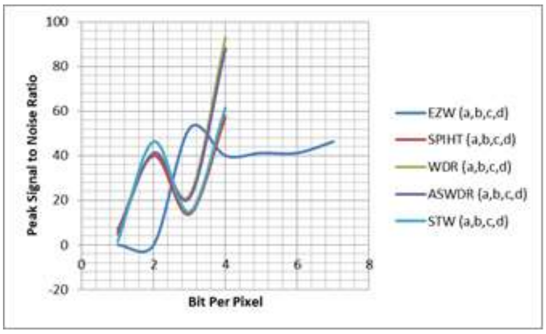

Figure 5b: Bit per Pixel vs.
Peak Signal to Noise Ratio for all.

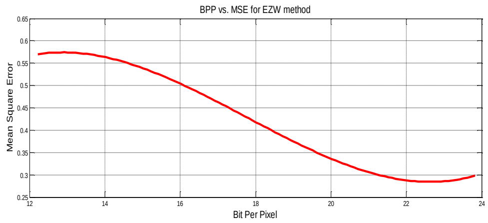

Figure 6a: BPP vs. MSE for EZW method .

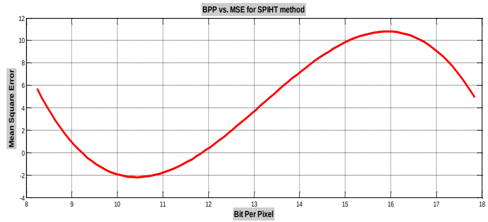

Figure 6b: BPP vs. MSE for SPIHT method.

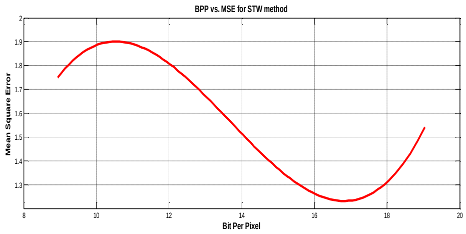

Figure 6c: BPP vs. MSE for STW method.

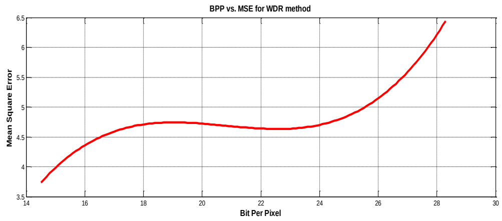

Figure 6d: BPP vs. MSE for WDR method.

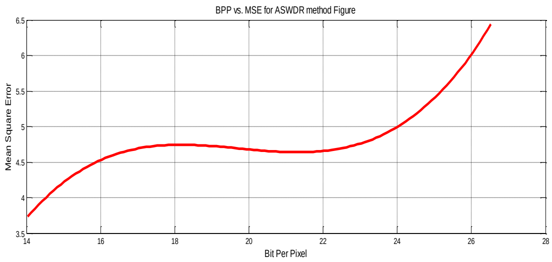

Figure 6e: BPP vs. MSE for ASWDR method Figure: 6 a- 6e .

Four test images were analyzed using five different compression techniques, as shown in Figure 7. The figure presents a graphical comparison of Bits Per Pixel (BPP) versus Mean Squared Error (MSE) for all methods. The results indicate that the EZW technique consistently achieves lower MSE values within the 14–28 BPP range, with MSE ranging from 0.28 to 0.57. In contrast, the other methods exhibit higher MSE values, reaching up to 6, highlighting the superior compression performance of EZW in maintaining image fidelity while reducing data size.

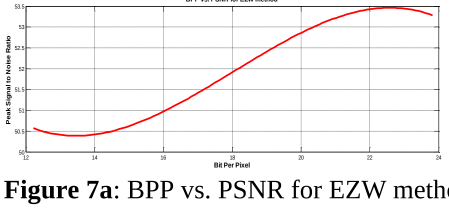

Figure 7a: BPP vs. PSNR for EZW method .

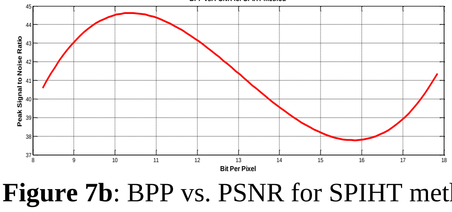

Figure 7b: BPP vs. PSNR for SPIHT method.

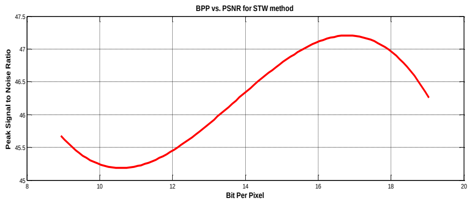

Figure 7c: BPP vs. PSNR for STW method.

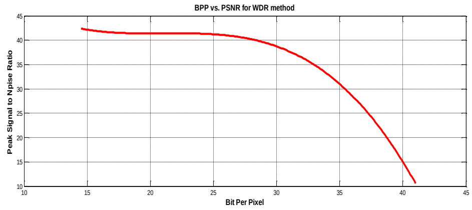

Figure 7d: BPP vs. PSNR for WDR method.

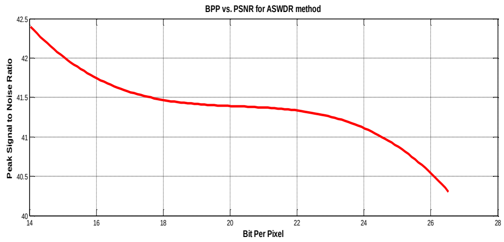

Figure 7e: BPP vs. PSNR for ASWDR method Figure 7a – 7e.

A graphical comparison of Bits Per Pixel (BPP) versus Peak Signal-to-Noise Ratio (PSNR) across all evaluated methods highlights the relationship between compression efficiency and image quality. The analysis demonstrates that the EZW technique consistently outperforms other approaches, achieving PSNR values of approximately 53.50 within a BPP range of 12.5 to 23.80. In comparison, the remaining methods yield PSNR values below 47.20 for the same BPP range, underscoring the superior signal fidelity of EZW. These results indicate that advanced coding schemes, particularly EZW, provide optimal performance by combining higher PSNR with lower BPP, confirming its effectiveness and efficiency relative to alternative methods.

Conclusion

This study investigated the impact of image content and compression ratios on performance across several wavelet-based algorithms, including WDR, ASWDR, STW, SPIHT, and EZW. Evaluation was conducted using objective metrics such as Peak Signal-to-Noise Ratio (PSNR), Mean Squared Error (MSE), and Bits Per Pixel (BPP) applied to the reconstructed images across diverse datasets. The results consistently demonstrated that the EZW technique outperformed the other methods, achieving higher PSNR values, lower MSE, and faster encoding times while maintaining high image quality. These findings confirm that, among the methods analyzed, EZW provides superior overall compression efficiency and image fidelity.

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