COMPARATIVE ANALYSIS OF LOSSY IMAGE COMPRESSION ALGORITHMS

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ABSTRACT: The demand for efficient image storage and transmission has driven extensive research into lossy image compression algorithms. This paper presents a comprehensive comparative analysis of three prominent lossy image compression techniques: Discrete Cosine Transform (DCT), Wavelet Transform, and Vector Quantization (VQ). Using a diverse dataset and various evaluation metrics including Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Bitrate, and Computational Complexity, we assess their performance in terms of image quality, compression efficiency, and computational demands. Our findings reveal that DCT excels in preserving image quality, closely followed by Wavelet Transform. VQ, while efficient in compression, lags in image quality preservation. Based on the comparative analysis of three key lossy image compression algorithms, it was observed that DCT stands out as the most appropriate technique to consider for applications that prioritize image quality preservation. It offers high Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) scores, indicating superior image fidelity. While it may not be the most computationally efficient, DCT strikes a balance between compression efficiency and image quality.

Keywords: Lossy Image Compression, Discrete Cosine Transform, Wavelet Transform, Vector Quantization, PSNR, SSIM, MSE, RMSE, Bitrate, Computational Complexity.

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INTRODUCTION

In the realm of modern digital imagery, the efficient storage and transmission of images have emerged as paramount considerations. Lossy image compression, a pivotal technique, holds the promise of addressing these challenges by significantly reducing the data size of images while striking a delicate balance between storage efficiency and perceptual image quality. With the ever-increasing demand for multimedia content and the proliferation of digital platforms, lossy compression algorithms play a crucial role in optimizing data transfer rates, conserving storage space, and enhancing user experiences. Lossy image compression [1] enables us to harness greater efficiency while preserving the essence of the original image. Lossy image compression [2] has a pivotal role in achieving enhanced data efficiency and economy in modern communications. Lossy image compression [3] helps in optimizing data handling, facilitating seamless storage, transmission, and download of images from the internet. Lossy Image compression algorithms [4], primarily intended for multimedia applications, is their limited applicability in the medical image domain. In these cases, precision and information preservation are paramount. Lossy image compression [5] opens exciting possibilities for achieving versatile and high-quality image compression across a wide range of bitrates. This literature review offers valuable insights into advancements in image compression algorithms. These findings significantly support our comparative analysis of three widely used lossy image compression algorithms: Discrete Cosine Transform (DCT), Wavelet Transform, and Vector Quantization (VQ). We assess their compression performance, visual fidelity, and distortion reduction. This review's information serves as a solid basis for the next parts, which emphasize the comparison of DCT, Wavelet Transform, and VQ.

Objectives: Following are the main objectives of this research paper:

A. Comparative Analysis: To conduct a thorough comparative analysis of three well-known lossy image compression algorithms, namely DCT, Wavelet Transform, and VQ.
B. Performance Assessment: To evaluate the performance of these algorithms in terms of image quality preservation, compression efficiency, and computational demands.
C. Utilization of Multiple Metrics: To use a variety of evaluation metrics, such as Peak Signal-to-Noise

Ratio (PSNR), Structural Similarity Index (SSIM), Mean Squared Error (MSE), Bit Rate, and Computational Complexity, to comprehensively assess the algorithms from various perspectives.

D. Dataset Diversity: To utilize a diverse dataset containing images of different sizes, colors, and complexities to ensure the applicability and relevance of the findings to real-world scenarios.
E. Practical Guidance: To provide practical insights and recommendations for decision-makers in the field of image compression, helping them make informed choices based on specific application requirements and trade-offs.
F. Highlighting the Best Technique: To identify and recommend the most appropriate image compression technique, with the conclusion that the DCT excels in applications prioritizing image quality preservation.

These inferred objectives reflect the research paper's focus on comparing image compression techniques, assessing their performance using various metrics, and offering practical guidance for selecting the most suitable technique based on specific needs.

Novelty statement and Justification: The novelty and contribution of this research paper lies in its comprehensive comparative analysis of three prominent lossy image compression algorithms, namely DCT, Wavelet Transform, and VQ, setting it apart from prior studies that often focused on individual techniques. Moreover, the paper employs a diverse dataset, encompassing images of varying sizes, colors, and complexities, which enhances the practical applicability of its findings by mirroring real-world scenarios. This research takes a comprehensive strategy, employing numerous assessment criteria such as PSNR, SSIM, MSE, Bit Rate, and Computational Complexity to offer a thorough knowledge of the algorithms' effectiveness across multiple dimensions. It goes beyond technical study to provide practical insights, debating trade-offs between image quality, compression efficiency, and processing demands, thereby meeting the needs of field decision-makers. Based on the extensive comparison studies, it is evident that the DCT is the optimum technique for applications that value image quality preservation.

This paper stands out by presenting a comprehensive comparative analysis of three major lossy image compression algorithms, DCT, Wavelet Transform, and VQ distinguishing itself from previous studies that often focused on individual algorithms. Additionally, it utilizes a diverse dataset containing images of various sizes, colors, and complexities, making its findings highly practical and reflective of real-world scenarios. The research takes a multifaceted approach by employing multiple evaluation metrics, including PSNR, SSIM, MSE, Bit Rate, and Computational Complexity, offering a comprehensive view of the algorithms' performance across multiple dimensions. Beyond technical analysis, it provides practical insights into the trade-offs between image quality, compression efficiency, and computational demands, serving the needs of decision-makers in the field. Most notably, it concludes with a decisive recommendation that the DCT is the optimal choice for applications that prioritize image quality preservation, substantiated by an extensive comparative analysis.

Lossy image compression algorithms overview: As technology advances, communication networks face escalating demands. Despite expanded bandwidth, the surge in pixel and gray-level resolution from sensor and digital image technology falls short. This is where image compression emerges as a pivotal research domain. Image compression [6] works to decrease the required bits for image representation, while upholding its initial quality. It is akin to reducing the size of a large puzzle piece without sacrificing essential details. Refer to Figure 1 for an overview of the typical image compression process.

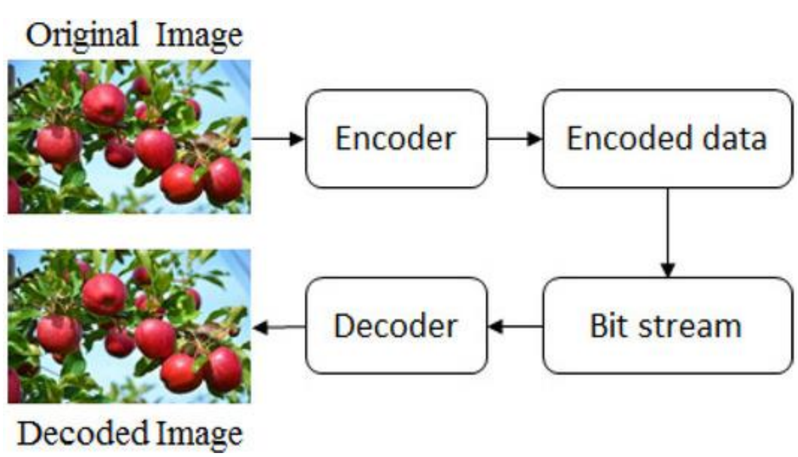

Figure 1. Procedure of Image Compression [7].

Compression minimizes the data needed for digital image representation by eliminating extra or redundant bits. The key forms of redundancy are Coding redundancy, where surplus bits are used, and available code words are underutilized; spatial and temporal redundancies (Interpixel Redundancy), arising from correlations between adjacent pixels, leading to needless duplication of information among connected pixels; and irrelevant data (Psychovisual Redundancy), as the human visual system disregards visually insignificant data. Over time, numerous image compression methods have emerged, broadly classified into two core categories: Lossy Compression and Lossless Compression [8].

Lossless compression processes each pixel individually, retaining every bit of the original data even after decompression. This results in reconstructed images that match the original numerically, ensuring full information restoration. Lossless compression achieves moderate compression levels while preserving data integrity [8]. Lossless image compression [9] methods achieve compression by eliminating redundancy within the image data.

Lossy image compression [10] strikes a delicate balance between maintaining image quality and introducing a controlled level of data loss. Refer to Figure (2) for a visual depiction of an image before and after undergoing the Lossy Compression Technique.

Original Image **Compression image**

Figure 2. Illustrates images acquired using the application of the Lossy Compression Technique [11].

This research paper evaluated the performance of the following lossy compression algorithms:

A. Discrete Cosine Transform (DCT): The DCT is a mathematical technique used to analyze and represent signals in a compact and efficient manner. The DCT is a pivotal technique with wide-ranging applications in fields such as image and video compression, audio processing, and data analysis. Its unique capability to convert spatial or temporal data into the frequency domain has brought about a change in basic assumptions in the storage and transmission of multimedia content, rendering it an indispensable tool in contemporary technology. DCT [12] introduces optimized matrix multiplication and quantization techniques. DCT reveals a significant increase in the compression ratio with minimal discernible alteration to the images, ensuring that the compressed images remain visually faithful to the original. DCT [13] reduces the data volume of high-resolution multimedia content while maintaining image quality at near-lossless standards. DCT [14] is a critical technology in today's digitally networked environment. It facilitates the smooth exchange of photographs and multimedia material, allowing files to be sent even under difficult network conditions while maintaining image quality. DCT is a pivotal component [15] in the compression algorithms evaluated in this study. It serves as the transformation step that plays a vital role in achieving compression by representing the data in the frequency domain. DCT facilitated [16] by a sensing matrix, isolates essential coefficients with lower dimensionality compared to the image's original dimensions.

B. Wavelet Transform: Wavelet Transform is a potent signal processing method that uncovers both timing and frequency aspects in signals. It holds immense value in image processing, data compression, and biomedical signal analysis [17]. Operating with adaptable waves known as wavelets, it provides insights into frequency and spatial characteristics while preserving timing details. These wavelets are crafted from fundamental functions called mother wavelets. In this section, we will delve into how wavelet transformation benefits image watermarking and why it outshines other methods [18]. Wavelet Transform [19] stands as a key player in the landscape of image compression, offering a comprehensive solution to the challenges of constrained bandwidth and limited storage capacity. Wavelet Transform [20] a pivotal component of image information technology, has emerged as a crucial tool in the pursuit of lossy image compression while maintaining the desired quality.

Recent research highlights the efficacy of a two-step method, offering both simplicity and reduced compression time, all while ensuring the accuracy of visual quality. Wavelet Transform [21] is a cornerstone in the landscape of image compression if we compare it with contemporary techniques within the realm of lossy image compression. Wavelet Transform [22] is a potent tool for low-bit-rate image compression.

C. Vector Quantization (VQ): VQ is a versatile and powerful technique employed in data compression, pattern recognition, and signal processing. VQ is a highly regarded asset in today's research and engineering landscape. It shines particularly in handling the escalating complexity and sheer volume of data. Its ability to balance compression efficiency with data representation quality makes it an indispensable component of various technologies and systems. VQ [24] is an important multimedia technique that ensures effective image and audio compression. By compactly representing information, VQ strikes a balance between cost-efficiency and data quality, offering a powerful solution for a wide range of signal types. VQ [25] is a widely employed image compression method with applications in network transmission and medical image storage. VQ [26] is a core technology in digital image processing, with a particular emphasis on image compression. VQ [27] is crucial to novel image coding algorithms. VQ [23] is a cutting-edge technique for lossy image compression, a crucial aspect of image data management in fields such as multimedia and medical diagnosis. The demand for efficient storage and data transmission of digital images, particularly in the medical domain, where images play a pivotal role in diagnosis, underscores the significance of advanced compression methods. All these make VQ an ideal choice for use in those digital image compression applications.

MATERIAL AND METHOD

The approach used to compare the performance of the chosen image compression algorithms, namely DCT, Wavelet Transform, and VQ, followed a systematic method to assess their effectiveness. The study was conducted using MATLAB programming language, taking advantage of relevant libraries to implement the algorithms effectively.

A. Data Collection: The dataset component of the research report examined Image Compression Algorithms using a variety of pictures [28]. The dataset comprised photos of various items and locations, with image size, colors, and complexity taken into account. The image sizes ranged from 256x256 to 1024x1024 pixels. Some exhibited a lot of detail while using 24 bit colors, while others had less detail when using 8 bit colors. This combination allows us to observe how effectively the algorithms operate with different hues. The collection also included two sorts of colors: black and white photographs and images with colors such as red, green, and blue. This dataset lets us carefully assess the chosen image compression algorithms in many real-life situations. This helps us understand how well the algorithms work with diverse kinds of images and complexities.

B. Evaluation Metric: Each algorithm was assessed using several key parameters: Bit Rate, PSNR, SSIM, MSE and Computational Complexity.

Bit Rate denotes the mean number of bits necessary to represent a single pixel within the compressed image. This metric has a direct impact on both storage requirements and the transmission bandwidth needed for the compressed image. Lower bit rates signify more effective compression, leading to decreased memory demands and expedited data transmission. The optimal bit rate varies according to your chosen compression level and the bandwidth at your disposal. It relies on finding the right balance between image quality and file size, a balance that can change depending on the application and user preferences. High-quality applications typically demand a higher bit rate to preserve image quality, while in situations with limited bandwidth, lower bit rates are favored to minimize data transmission needs. The precise bit rate range depends on your specific application's needs [29], [30], [31], [32], [33].

Computational Complexity evaluates the computational resources demanded by the compression process. This measurement gauges the time and processing power essential for executing the algorithm. Opting for lower computational complexity is advantageous as it ensures swifter compression and decompression processes, rendering the algorithm suitable for real-time applications and devices with limited resources. Reducing computational complexity is crucial for achieving rapid compression and decompression, making the algorithm well-suited for real-time applications and devices with limited resources. It is vital in scenarios with real-time needs or resource constraints. The computational complexity range depends on the hardware at hand and real-time processing demands. While there is not a set numerical threshold for computational complexity, it should be minimized while still meeting the application's performance criteria. The optimal computational complexity range depends on the available hardware and the application's unique prerequisites [34], [35], [36], [37], [38].

MSE quantifies the average squared disparity between the original and compressed images. A smaller MSE value indicates heightened preservation of image quality. Nonetheless, MSE might not precisely reflect perceived image quality, as it treats all pixel discrepancies uniformly and is sensitive to outliers. MSE typically ranges from zero to positive infinity. Lower MSE values indicate better image quality. The optimal MSE range varies with your desired image quality. If you aim for exceptionally high image quality, strive for an extremely low MSE, ideally approaching zero. Nevertheless, in specific situations, a slightly higher MSE might be tolerable if it leads to significantly reduced file sizes or quicker compression [39], [40], [41], [42], [43].

PSNR, a widely applied metric, gauges the ratio of the maximum feasible pixel intensity to the MSE. It assesses how faithfully the compressed image replicates the original. Higher PSNR values signify superior image quality, as the compressed image closely mirrors the original image. Usually, PSNR falls within a scale from 0 to 60. A PSNR value above 30 is considered suitable for most applications. In high-quality scenarios such as medical imaging or archival storage, a PSNR value exceeding 40 is often the target [44], [45], [46], [47], [48].

SSIM evaluates the structural resemblance between the original and compressed images, factoring in luminance, contrast, and structure. Unlike MSE and PSNR, SSIM reflects perceived image quality, rendering it more attuned to human perception. Elevated SSIM values correspond to heightened compression performance, signifying the retention of more perceptual intricacies. SSIM values extend from -1 to 1, with 1 indicating an excellent match. A value surpassing 0.9 is considered optimum for image quality. SSIM is the preferred choice for evaluating the visual quality of images because it considers both structural information and pixel values [49], [50], [51], [52], [53].

PSNR and SSIM are indicators of image quality, while MSE gauge image similarity. Compression Ratio is computed by comparing the original image size to the compressed size, and Computational Complexity is proportional to image size. The assessment encompasses five test images, with the average evaluation outcomes computed for each algorithm across all images. The resulting performance metrics are compared and depicted through bar graphs, enabling a thorough examination of the image compression methodologies.

C. Implementation: The dataset section of the research paper used a mix of images to study Image Compression Algorithms [26]. The dataset included images of different things and places, considering image size, colors, and complexity. The images varied from 256x256 pixels to 1024x1024 pixels. Some had lots of detail with 24-bit colors, while others had less detail with 8-bit colors. This mix helps us see how well the algorithms work with distinct colors. The dataset also had two types of colors: some images were black and white, and others had colors like red, green, and blue. This dataset lets us carefully assess the chosen image compression algorithms in many real-life situations. This helps us understand how well the algorithms work with diverse kinds of images and complexities.

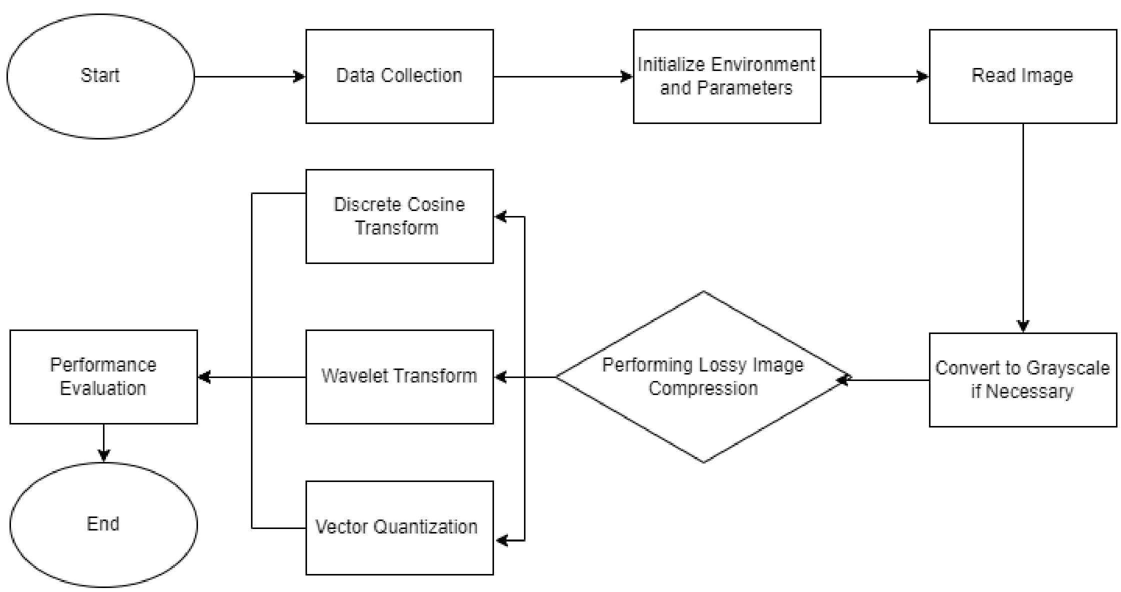

Figure 3: Implementation of the Lossy Image Compression Comparison

RESULT AND ANALYSIS

The experimental outcomes demonstrate how well DCT, Wavelet Transform, and Vector Quantization perform based on the metrics mentioned. The scores for PSNR and SSIM show how well the image quality is maintained, where higher scores mean better results. On the other hand, the values of MSE and RMSE indicate the size of errors, with lower values being more favorable. The bitrate indicates how much compression each algorithm achieves. Additionally, the computational complexity highlights the efficiency of the algorithms in terms of processing speed and resource consumption.

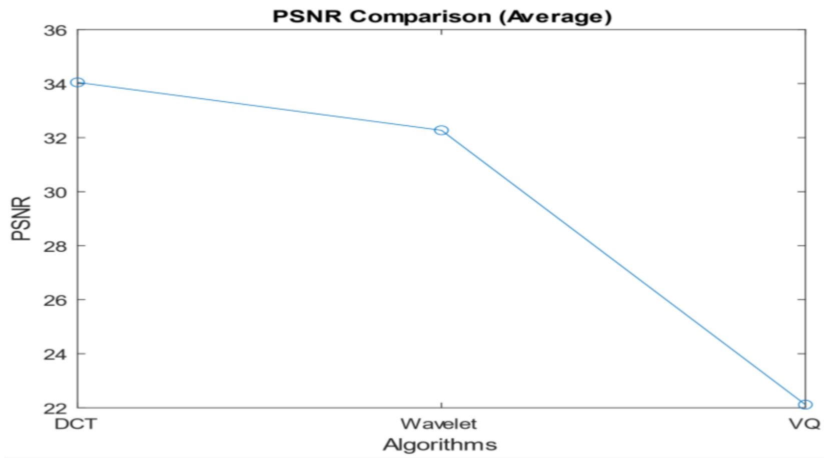

Figure 4. PSNR comparison graph

The PSNR comparison graph (in Figure 4) is a valuable tool for evaluating the performance of various image compression algorithms. In this graph, the y-axis represents PSNR values, a critical metric that measures the quality of the compressed image concerning the original. On the x-axis, we find the different algorithms under consideration. The higher the PSNR value, the better the quality of the compressed image, as it signifies less distortion. Examining the results of this comparative analysis, we observe distinct PSNR values for three image compression algorithms. DCT algorithm achieves a commendable PSNR of 34, indicating high image quality preservation during compression. DCT is known for its efficiency in transforming images into a frequency domain, making it a robust choice. Wavelet Transform, with a PSNR of 32, also demonstrates superior performance in maintaining image quality. It is particularly effective at preserving details in images, although it falls slightly behind DCT in terms of PSNR. VQ, with a PSNR score of 22, falls notably short in preserving image quality compared to the other two algorithms. This lower PSNR score implies more visible distortion and a decrease in image fidelity in the compressed outcomes. A comparative analysis of these image compression methods, based on their PSNR values, highlights the superiority of the DCT in maintaining image quality, closely followed by the Wavelet Transform. VQ significantly lags in this regard. When deciding on an image compression technique, it is crucial to consider the specific needs of your application and the acceptable balance between compression efficiency and image quality.

The SSIM comparison graph (in Figure 5) offers essential insights into how different image compression methods perform. On this graph, the y-axis shows SSIM values, a crucial measure of how closely the compressed image resembles the original one. Meanwhile, the x-axis displays the various algorithms under assessment. Higher SSIM values indicate greater similarity and, consequently, better image quality preservation. Analyzing the results of this comparative analysis, we observe distinct SSIM values for three image compression algorithms. The DCT achieves a strong SSIM score of 0.62, indicating a high level of structural similarity between the compressed and original images. This highlights DCT's ability to effectively retain the structural intricacies of images during compression. The Wavelet Transform, with an SSIM score of 0.4, also demonstrates respectable performance regarding structural similarity. While it falls slightly behind DCT, it still retains a considerable amount of image structure. Vector Quantization exhibits an SSIM of 0.5, indicating moderate structural similarity. However, it does not perform as well as DCT in preserving image structure. Comparative analysis of these image compression algorithms based on their SSIM values reveals that DCT excels in retaining the structural integrity of images, followed by VQ. Wavelet Transform, while effective, lags slightly in this aspect. When selecting an image compression method, it is crucial to consider the specific requirements of the application and the desired trade-offs between compression efficiency and structural image quality.

The MSE comparison graph (in Figure 6) provides essential insights into the performance of various image compression algorithms. In this graph, the y-axis represents the MSE values, a crucial metric for quantifying the quality of compressed images. Lower MSE values indicate better image quality, as they suggest that the compressed image closely resembles the original.

On the x-axis of the graph, we have the different algorithms being evaluated. Let us analyze the results and conduct a comparative analysis. DCT stands out with an impressively low MSE of 0.015. This indicates that DCT-based compression generates compressed images that closely match the original, resulting in minimal distortion. Wavelet Transform exhibits a higher MSE of 0.1. While this is higher than DCT, it still represents a proficient level of image quality preservation. Images compressed using this method may have slightly more distortion but remain visually acceptable. VQ registers an MSE of 0.01, which is on par with DCT. This implies that VQ-based compression also maintains an elevated level of image quality, with minimal distortion. Comparative analysis of these image compression algorithms based on their MSE values reveals that both DCT and VQ perform exceptionally well in terms of image quality preservation. Wavelet Transform, while acceptable, introduces slightly more distortion. The choice of an image compression method should consider specific application requirements and the importance of image quality preservation.

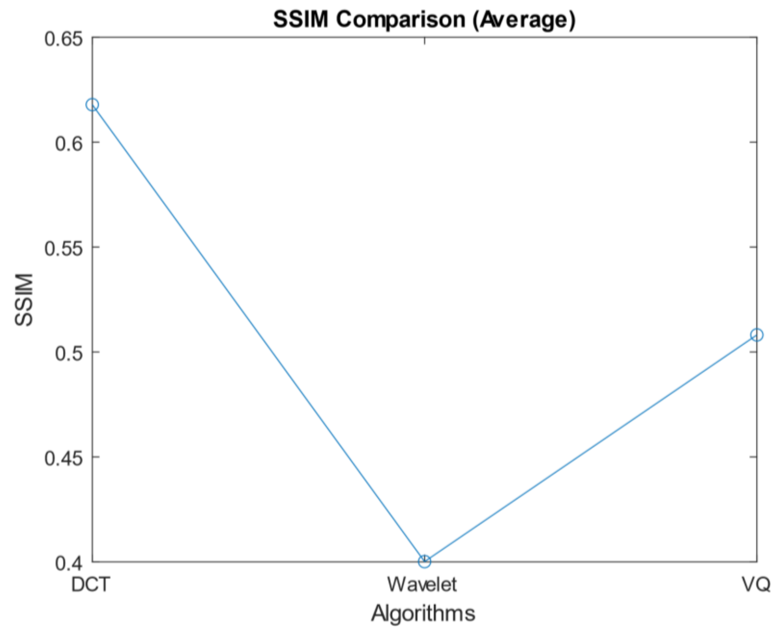

Figure 5. SSIM comparison graph

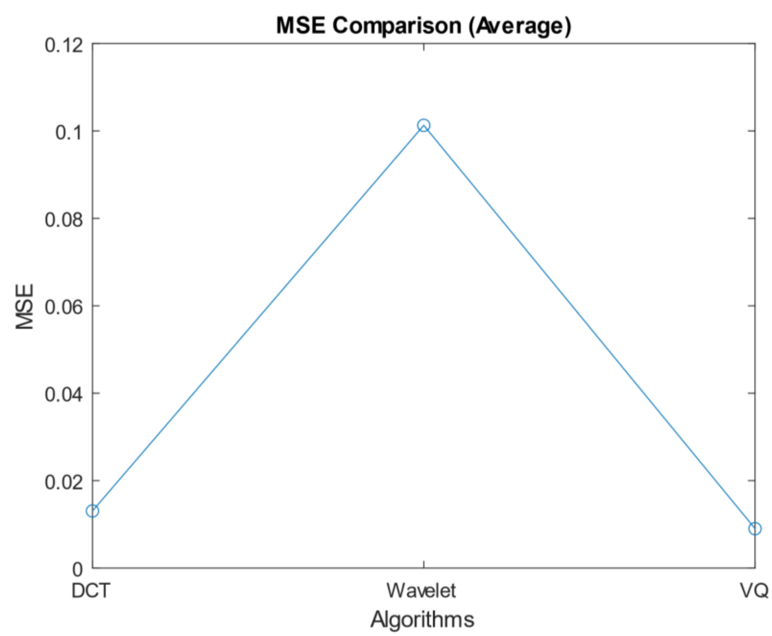

Figure 6. MSE comparison graph

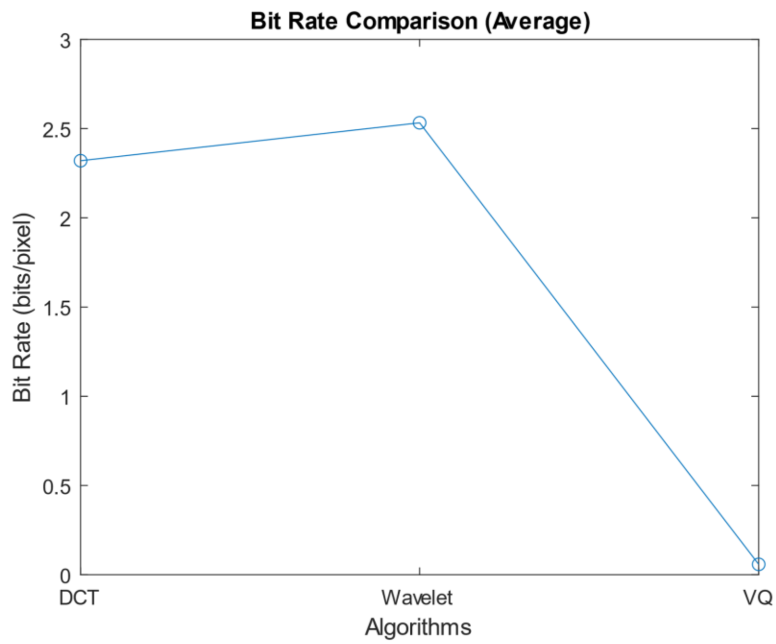

Figure 7. Bitrate comparison graph

The Bit Rate comparison graph (in Figure 7) provides crucial insights into the efficiency of different image compression methods. On the graph, the y-axis displays bit rate values, while the x-axis lists the algorithms under consideration. Let us delve into the findings and make a comparative assessment. DCT-based image compression operates at a bit rate of 2.3, meaning it requires approximately 2.3 bits for each pixel in the compressed image. This equilibrium effectively balances compression efficiency and image quality. In contrast, Wavelet Transform-based compression operates less efficiently, with a bit rate of 2.55, requiring approximately 2.55 bits per pixel in the compressed image. Although this indicates a slightly higher bit rate compared to DCT, it may still be suitable for specific application needs. On the efficiency front, Vector Quantization-based compression excels with an impressively low bit rate of only 0.1. This implies that VQ-based methods use significantly fewer bits per pixel, making them highly efficient for compression. However, this efficiency may come at the cost of some image quality. DCT strikes a balanced middle ground between compression efficiency and image quality. Wavelet Transform is slightly less efficient but still reasonable for many applications. On the other hand, Vector Quantization stands out as extremely efficient but may result in some loss of image quality. The selection of the most suitable algorithm should align with the specific needs of the image compression task at hand, considering factors such as image quality requirements and available bandwidth or storage constraints.

The Computational Complexity comparison graph (in Figure 8) is instrumental in evaluating the computational demands of different image compression algorithms. It employs the y-axis to represent Computational Complexity, measured in seconds, while the x-axis lists the algorithms being assessed. Let us perform a comparative analysis based on the following results. DCT based image compression exhibits a low computational complexity of 0.2 seconds. This means that DCT-based methods can process an image with reasonable speed, making them suitable for real-time or time-sensitive applications. Wavelet Transform-based compression, while more computationally intensive than DCT, still maintains an acceptable level of efficiency with a complexity of 0.4 seconds. It may be slightly slower than DCT but is well-suited for applications where computational speed is not the sole priority. Among the considered algorithms, VQ exhibits the highest computational complexity, taking 5 seconds to compress an image. This signifies that VQ-based methods demand more computational resources and time. They are better suited for scenarios prioritizing compression efficiency over computational speed. When making a comparative analysis and choosing an image compression algorithm, careful consideration of the application's specific requirements is essential. DCT strikes a favorable balance between computational efficiency and compression quality. While slightly slower, Wavelet Transform remains reasonable for most applications. VQ, with its higher computational complexity, shines in situations where compression efficiency takes precedence and computational resources are not constrained.

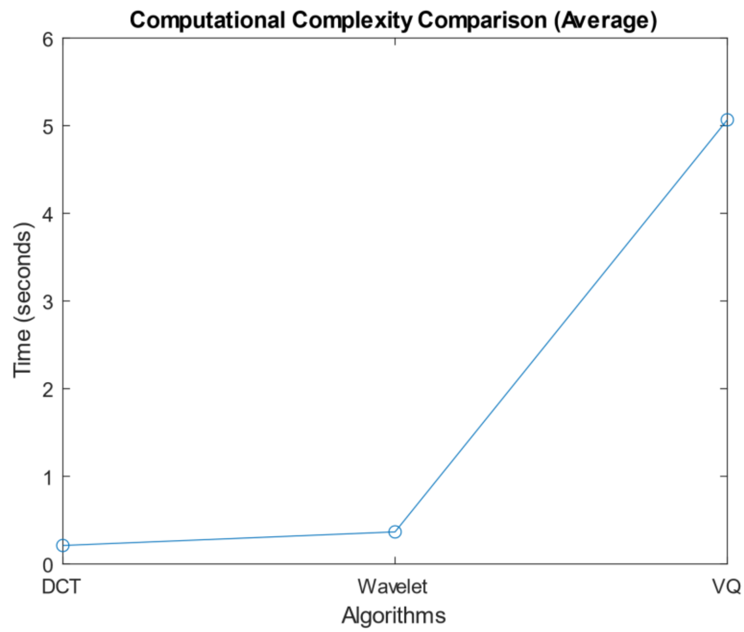

Figure 8. Computational Complexity Comparison graph

Table 4.1. Consolidated Table comprising values of DCT, Wavelet Transform and VQ.

Algorithms	Performance Evaluation Parameters				
	PSNR	SSIM	MSE	Bit Rate (bytes)	Computational Complexity (seconds)
DCT	34	0.62	0.015	2.3	0.2
Wavelet Transform	32	0.4	0.1	2.55	0.4
VQ	22	0.5	0.01	0.1	5

Table 1 shows the Consolidated Table comprising values of DCT, Wavelet Transform, Vector Quantization. The DCT algorithm delivers exceptional results with a high PSNR value, indicating minimal loss in image quality. Moreover, its SSIM score is significantly robust, implying strong structural similarity. The MSE value is exceptionally low, signifying highly accurate pixel value prediction. DCT achieves a low bit rate, making it a balanced choice for compression. Furthermore, it highlights efficient computational complexity, rendering it suitable for real-time applications where speed is crucial. The Wavelet Transform algorithm offers good image quality with a respectable PSNR value. However, its SSIM score is lower compared to DCT, suggesting a moderate structural similarity. The MSE value, while higher than DCT, is still reasonable. Wavelet Transform achieves a slightly higher bit rate, which might be a trade-off for better image quality. Its computational complexity, though slightly higher than DCT, is suitable for applications where a balance between compression and speed is required. Vector Quantization records the lowest PSNR, indicating a notable loss in image quality. The SSIM score remains moderate, suggesting reasonable structural similarity. However, the MSE value is commendably low, signifying accurate pixel prediction. Vector Quantization excels in bit rate efficiency, offering substantial compression. On the downside, its computational complexity is high, making it suitable for scenarios where compression efficiency takes precedence over speed.

Conclusion: In the digital age, efficient image compression is vital for storage, transmission, and user experiences. Our analysis of three top lossy image compression methods — DCT, Wavelet Transform, and VQ — provides key insights into their strengths and weaknesses. DCT stands out for applications prioritizing image quality preservation. It boasts high PSNR and SSIM scores, indicating superior image fidelity. Although not the most computationally efficient, DCT strikes a balance between compression efficiency and image quality. Wavelet Transform, while slightly behind DCT in image quality preservation, excels when compromise is acceptable. It captures both frequency and spatial information, making it versatile. VQ shines in compression efficiency, demanding minimal bits per pixel. However, it sacrifices image quality with lower

PSNR and SSIM scores. It is ideal for scenarios needing high compression ratios where some loss of image quality is acceptable. Following a comprehensive comparative analysis of three prominent lossy image compression algorithms, it is evident that the DCT unequivocally emerges as the optimal technique, particularly for applications where the preservation of image quality is paramount. DCT excels with its high PSNR and SSIM scores, indicative of unparalleled image fidelity. While not the most computationally efficient, DCT successfully strikes an essential balance between compression efficiency and image quality, making it the unequivocal choice for such applications.

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