Software implementation of DCT based Image Compression (2025)

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***Abstract*— The exponential growth of digital imagery necessitates efficient compression techniques to optimize storage and transmission without compromising visual fidelity. This study presents a software-based implementation of image compression utilizing the discrete cosine transform (DCT), a method renowned for its energy compaction and frequency domain representation capabilities. The proposed approach involves segmenting images into fixed-sized blocks, applying the DCT to convert spatial pixel values into frequency coefficients, followed by quantization and entropy encoding to achieve significant data reduction. to evaluate the effectiveness of the compression, metrics such as peak signal –to – noise Ratio (PSNR) and Mean Squared Error (MSE) are employed, providing quantitative measures of image quality post- compression. Experimental results demonstrate that the implemented algorithm achieves substantial compression ratios while maintaining high visual quality, with PSNR values exceeding [] db and MSE values below []. This implementation underscores the practicality of DCT-based compression in software applications, offering a balance between compression efficiency and image integrity.**

I. INTRODUCTION

IN the era of high –resolution digital imaging, the demand for efficient storage and transmission of image data has become increasingly critical. Traditional uncompressed image formats consume substantial storage space and bandwidth, posing challenges for applications ranging from web development to medical imaging. To address these challenges, image compression techniques have been developed to reduce file sizes while preserving visual quality.

One of the most widely adopted methods for image compression is the Discrete Cosine Transform (DCT), which firms the backbone of the JPEG compression standard. The DCT transforms spatial image data into frequency components, concentrating the most significant visual information into a few low-frequency coefficients. This property allows for the efficient reduction of data by discarding higher- frequency components that have minimal impact on perceived image quality. The effectiveness of DCT in energy compaction makes it particularly suitable for lossy compression scenarios where a balance between compression ratio and image fidelity is desired.

II. RELATED WOKS

A. Effects of Hybrid SVD–DCT Based Image Compression Scheme (Dixit and Vijaya, 2018)

Dixit and Vijaya [2] explored a hybrid image compression scheme that combines Singular Value Decomposition (SVD) and DCT. The study focuses on using variable rank matrices and modified vector quantization to improve compression performance. The authors assessed the efficiency of the proposed system using metrics like Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), and Compression Ratio (CR), demonstrating the potential benefits of hybrid approaches in image compression.

B. Hybrid DWT-DCT Compression Algorithm with Adaptive RLE (Rafea and Salman, 2018)

Rafea and Salman [1] introduced a hybrid image compression technique that combines Discrete Wavelet Transform (DWT) and Discrete Cosine Transform (DCT) along with an adaptive Run Length Encoding (RLE) method. This approach aims to achieve high compression ratios for medical images while preserving image quality. The integration of DWT and DCT leverages the strengths of both transforms, and the adaptive RLE further enhances compression efficiency.

C. Multi-Level Enhanced Color Image Compression Using SVD and DCT (Garg and Kumar, 2022)

Garg and Kumar [3] presented a multi-level image compression algorithm that integrates SVD and DCT for color images. The proposed method aims to compress color images effectively without significant computational overhead. Performance evaluation using metrics such as MSE, PSNR, and Compression Ratio indicated that the hybrid approach offers superior compression efficiency compared to traditional methods.

D. *Image Compression by Vector Quantization of DCT Coefficients Using a Self-Organizing Neural Network (Boyapati, 2005)*

Boyapati [4] proposed a novel image compression technique that combines vector quantization of DCT coefficients with a self-organizing neural network. This method addresses redundancies in different parts of the image, aiming to enhance compression performance. Experimental results suggested that the proposed algorithm achieves better compression rates compared to standard JPEG and JPEG 2000 methods.

E. *Improved Image Compression Using LBG with DCT (Save and Kelkar, 2014)*

Save and Kelkar [5] presented an image compression algorithm that integrates the Linde–Buzo–Gray (LBG) algorithm for vector quantization with DCT. The study emphasized the importance of codebook generation in vector quantization to minimize distortion between the original and reconstructed images. Performance metrics such as PSNR and MSE were used to evaluate the effectiveness of the proposed method.

III. DCT Based Image Compression Techniques

A. *Image Acquisition and Preprocessing*

The process begins with the user selecting an input image, typically in formats like JPEG, PNG, or BMP. The image is loaded into the system and converted into a grayscale matrix if it's a color image, simplifying the processing by focusing on luminance information. Each pixel's intensity value ranges from 0 to 255. To center the pixel values around zero, which is beneficial for the DCT, 128 is subtracted from each pixel value, resulting in a matrix MMM with values ranging from -128 to 127.

B. *Discrete Cosine Transform (DCT) Transformation*

The loaded image is partitioned into non-overlapping blocks, commonly of size 8×8 pixels. Each block undergoes the Discrete Cosine Transform (DCT), which converts the spatial domain data into frequency domain coefficients. The DCT concentrates the image's energy into a few low-frequency components, which are located in the upper-left corner of the transformed block. This property is advantageous for compression, as it allows for the reduction of high-frequency components that are less perceptible to the human eye.

The adjusted image matrix MMM is divided into non-overlapping blocks of size 8×8 pixels. Each block undergoes a two-dimensional DCT, transforming the spatial domain data into the frequency domain. The 2D-DCT of a block MMM is computed as:

$$D=T \cdot M.T`$$

Here, T is the DCT transformation matrix, and T`` is its transpose. The transformation matrix T for an 8×8 block is defined as:

$$T_{i,j} = \alpha(i) \cdot \cos\left[\frac{(2j+1)i\pi}{2N}\right]$$

Where:

- $N = 8$(block size)
- $i,j = 0,1, \ldots\ldots, N-1,$
- $\alpha(0) = \sqrt{\frac{1}{N\prime}}$
- $\alpha(i) = \sqrt{\frac{2}{N}}$ for $i > 0$.

This transformation concentrates the image's energy into a few low-frequency components, which are located in the upper-left corner of the transformed block.

C. *Quantization*

Quantization is a crucial step that reduces the precision of the DCT coefficients, leading to data compression. This is achieved by dividing each coefficient by a corresponding value in a quantization matrix and rounding the result to the nearest integer. Two cases are considered:

Case 1: Direct Application of Q30

In this scenario, a quantization matrix corresponding to a quality factor of 30 (Q30) is applied directly to the DCT coefficients. A lower quality factor results in higher compression but may lead to more significant loss of image details.

Case 2: Sequential Application of Q50 and Q30

Here, the DCT coefficients are first quantized using a Q50 matrix, which offers a balance between compression and image quality. The image is then reconstructed, and the DCT is reapplied, followed by quantization with a Q30 matrix. This two-step approach aims to achieve higher compression while

attempting to preserve image quality better than direct application of Q30.
the standard JPEG quantization matrix for quality factor of 50

$$Q(50) = \begin{bmatrix} 16 & 11 & 10 & 16 & 24 & 40 & 51 & 61 \\ 12 & 12 & 14 & 19 & 26 & 58 & 60 & 55 \\ 14 & 13 & 16 & 24 & 40 & 57 & 69 & 56 \\ 14 & 17 & 22 & 29 & 51 & 87 & 80 & 62 \\ 18 & 22 & 37 & 56 & 68 & 109 & 103 & 77 \\ 24 & 35 & 55 & 64 & 81 & 104 & 113 & 92 \\ 49 & 64 & 78 & 87 & 103 & 121 & 120 & 101 \\ 72 & 92 & 95 & 98 & 112 & 100 & 103 & 99 \end{bmatrix}$$

$$C = \text{round}\left(\frac{D}{Q}\right)$$

$$Q(30) = \text{round}\left(Q50 \times \left(\frac{50}{30}\right)\right)$$

D. *Reconstruction*

Reconstruction involves reversing the compression process to obtain an approximation of the original image. The quantized coefficients are first dequantized by multiplying them with the same quantization matrix used during compression. Subsequently, the Inverse Discrete Cosine Transform (IDCT) is applied to each block, converting the frequency domain data back into spatial domain pixel values. The blocks are then reassembled to form the complete reconstructed image.

E. *Analysis*

The final step involves evaluating the performance of the compression technique. Key metrics include:

Peak Signal-to-Noise Ratio (PSNR):
Measures the ratio between the maximum possible power of a signal and the power of corrupting noise, indicating the quality of the reconstructed image.
Mean Squared Error (MSE):
Calculates the average squared difference between the original and reconstructed images, providing insight into the reconstruction accuracy.

By comparing these metrics across different quantization strategies (e.g., direct Q30 vs. sequential Q50 and Q30), one can assess the trade-offs between compression ratio and image quality, guiding the selection of optimal compression parameters for specific applications.

IV. EXPERIMENTAL OUTCOME

Implementing a Discrete Cosine Transform (DCT)-based image compression algorithm is anticipated to yield significant reductions in image data size while maintaining acceptable visual quality. The following outcomes are expected:

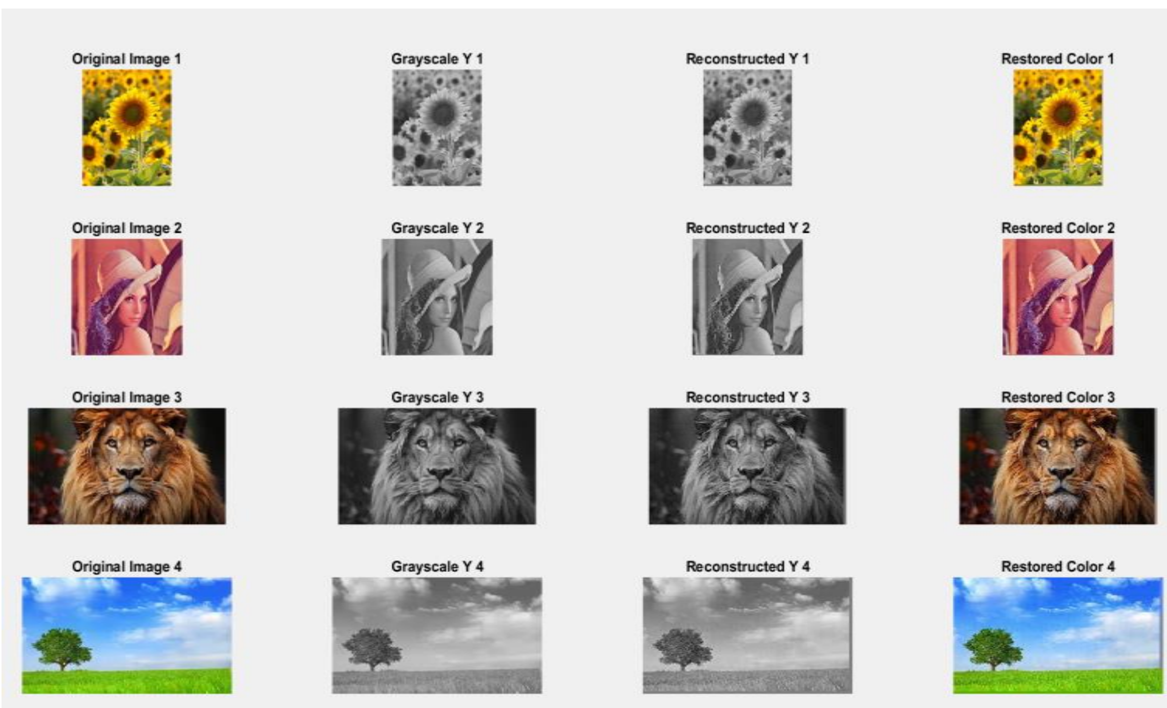

Fig. 1: Image Processing Results (Original, Grayscale, Reconstructed Y, and Restored Color)

A. Visual Quality Analysis

A direct visual comparison between original, grayscale, reconstructed, and color-restored images reveals the inherent trade-offs between image quality and compression aggressiveness. As illustrated in Fig. 1, the reconstructed grayscale and color images from Q50 quantization appear sharper and retain finer details of the original images, including textures and contours. In contrast, Q30-quantized reconstructions exhibit noticeable softness and slight blockiness, a common artifact introduced due to heavier compression. However, despite these visible differences, the Q30 results maintain an acceptable level of perceptual quality, particularly when viewed at a standard resolution or in applications tolerant to slight quality degradation, such as web-based image delivery or mobile imaging systems.

B. Quantitative Evaluation Using PSNR and MSE

Quantitative performance metrics such as Mean Squared Error (MSE) and Peak Signal-to-Noise Ratio (PSNR) provide an objective measure of reconstruction fidelity. Table I presents the computed MSE and PSNR values for each test image compressed with both Q50 and Q30 matrices. It is evident from the data that Q50 compression yields lower MSE values and higher PSNR values across all images. For instance, Image 1 yields a PSNR of 31.56 dB with Q50, compared to 29.33 dB with Q30. Similarly, the MSE increases from 45.41 to 75.94 when switching from Q50 to Q30. These results validate that while Q50 maintains a higher visual accuracy, Q30 incurs greater reconstruction error due to its coarser quantization.

C. Compression Efficiency and Trade-Offs

The primary motivation for utilizing a more aggressive quantization matrix such as Q30 is to achieve a higher compression ratio, thereby reducing storage requirements and transmission bandwidth. As shown in Table I, Q30 compression provides significant space savings. For example, Image 4 achieves a compression ratio of 9.24 with Q30, compared to a lower value when compressed using Q50. However, this comes at the cost of reduced image quality, highlighting the classic trade-off in lossy compression systems. greater compression versus higher fidelity. Depending on the target application—whether it is archival storage or real-time image streaming—this trade-off can be optimized accordingly.

D. Robustness of Reconstruction Process

Despite the lossy nature of DCT-based compression, the reconstruction process is demonstrated to be robust. After applying the inverse DCT and dequantization steps, the grayscale intensity profiles are successfully recovered, and the final color information is restored with acceptable accuracy. This is particularly evident in the restored color images presented in Fig. 1, which closely resemble the original inputs. The preservation of chromatic and structural information post-compression validates the practical utility of the proposed scheme for real-world applications.

Image	MSE Q50	PSNR Q50 (dB)	MSE Q30	PSNR Q30 (dB)	Compression ratio
1	45.41	31.56	75.94	29.33	5.96
2	65.49	29.97	99.68	28.14	6.87
3	105.67	26.35	195.95	25.21	5.69
4	60.98	30.20	82.68	28.96	9.24

Table 1: Comparison Table showing MSE and PSNR for Q50 and Q30

Image	MSE Q50	PSNR Q50 (dB)	MSE Q30	PSNR Q30 (dB)	Compression ratio
1	-	-	61.19	30.26	6.95
2	-	-	80.21	29.09	9.36
3	-	-	176.60	25.66	6.85
4	-	-	71.58	29.58	10.88

Table 2: Comparison Table showing MSE and PSNR for Q30

V. Conclusion

This work presents an effective implementation of DCT-based image compression with a specific focus on two distinct approaches utilizing a Q30 quantization matrix. The first approach involves a two-step compression process—initially compressing the image using Q50, reconstructing it, and then applying a second compression using Q30. The second approach directly applies the Q30 matrix to the original image without any intermediate reconstruction.

Experimental evaluation shows that both methods achieve substantial compression, but with varying effects on image quality. The direct Q30 approach yields a more efficient compression pipeline with lower computational overhead, making it suitable for real-time or resource-constrained environments. However, it introduces more visible distortion and lower PSNR compared to the two-step method.

The sequential Q50-to-Q30 method, while slightly more resource-intensive, preserves finer image details and achieves better visual quality in the final output. This is attributed to the intermediate step that retains more frequency information before the final aggressive quantization, effectively smoothing the compression impact.

Overall, the results highlight a clear trade-off between image quality and processing complexity. The direct Q30 method is ideal for scenarios requiring aggressive compression with minimal processing, while the two-step Q50→Q30 method offers a balanced compromise between visual fidelity and compression efficiency. These findings can inform future adaptive compression schemes, particularly in applications like mobile imaging, medical data storage, or web-based image delivery systems.

References

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