

Adaptive Lossy Color Image Compression System Based on Hybrid Algorithm

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Abstract

As the digital age progresses, multimedia technologies have become commonplace, with users expecting high-quality audio, video, and image content across various platforms and devices. As a result, the quantity of data produced by these multimedia programs has grown substantially. Also, the explosive growth in the use of multimedia has led to a rise in the quantity of images that are used and created, which creates challenges, in relation to the requirement for increased storage capacity and enhanced data transport speed. To address these challenges, image compression has emerged as a critical solution by decreasing the volume of the image without significantly degrading their quality. As technology advances further, the need for more image compression techniques will become more important. This paper presents a hybrid lossy image compression system by using four compression techniques which are Bit plane slicing, Discrete wavelet transform (DWT), Discrete cosine transform (DCT), and Arithmetic coding. To implement this proposed method three experiments were performed by using images of varying dimensions, namely (256 * 256), (512 * 512), and (1024 * 1024) and four different quantization coefficients. For efficiency performance measurement of the proposed system, three metrics were used: Peak signal-to-noise ratio (PSNR), Structural similarity index (SSIM), and compression ratio (CR). The results showed that the proposed hybrid system was successful in raising the compression ratio in comparison with standard JPEG as the CR when using jpeg reached 35%, while the suggested system provided a higher CR of 62% with keeping a satisfactory level of image quality.

Keywords: Arithmetic coding, Bit plane slicing, CR, DCT, DWT, Image Compression, PSNR, SSIM.

Introduction

Online communication has played an important role in our lives, and with the increase of social media applications, the amount of data consumed has increased rapidly. The image is at the core of social media because it represents the information in an easy way and makes it easier to understand in comparison with the text. As the adage says, "A picture is worth a thousand words"¹. Despite the

necessity of utilizing images to convey information, the rising usage of digital devices like computers, mobiles, and social media apps increased data consumption. Our cyber world generates 2.5 quintillion bytes of data daily². The International Data Corporation predicts a rise in global data from 40 zettabytes in 2019 to 175 zettabytes in 2025 where (1 zettabyte = 10²¹ bytes)³. Images are now widely

used as documents, and to use them in a variety of applications, it is sometimes important to compress them first. Redundant information is included in all images. When there is redundancy in a picture, information is stored more than once. It might be a pattern that appears repeatedly in the picture, or it could be a series of pixels that keep reappearing. Redundancy removal is a useful technique for decreasing an image's file size. When one or more of these inefficiencies are fixed, we may say that an image has been compressed. Large data files, such as photographs, may be compressed with the use of newly discovered compression methods⁴. To save the massive amounts of image data produced by modern technology, it is necessary to use effective procedures that typically succeed in compressing images. Generally, in the field of image compression, there are typically two primary techniques that are

employed: lossless and lossy image compression. Lossless compression refers to a technique utilized to decrease the file size of an image with preserving its visual fidelity, where there is no loss in the image information transformation from the original to the compressed version. Therefore, the lossless technique is used in various applications. Applications of lossless image compression include Archiving medical and business records, where a loss of information in the original picture could lead to an inaccurate diagnosis, use lossless image compression⁵. Whereas, lossy is a technique that involves compressing the image with some reduction in quality but with a high compression ratio. Lossy works best in applications that do not require a high level of clarity and image quality, such as web design, digital photography, and multimedia applications⁶.

Related Work

In recent years, many studies have been performed to obtain a good image compression ratio with good image quality. Gahalot and Mehra⁷ proposed a hybrid image compression system that utilized DCT, run-length encoding (RLE), and Huffman coding techniques for achieving lossless compression and the system was implemented on the YUV color space image. The findings achieved high compression rate range from 8% to 36%. Al-khafaji and Al-Kazaz⁸ proposed a hybrid color picture compression technique by utilizing inter-differentiation through the application of a one-level DWT and polynomial coding. The findings indicate that a significant CR was attained on the RGB image by the utilization of spectral and bands redundancy. Yusra et al.⁹ employed a lossy hybrid system that was built upon the YUV color transformation model. This system utilized the Haar DWT as the base and the set partitioning in hierarchical trees (SPIHT) algorithm. The findings revealed that the average CR surpassed a range of 4 to 16. Al-Hadithy et al.¹⁰ introduced an Adaptive 1-D Polynomial Coding technique for compressing medical grayscale images. Their approach utilizes a novel compression strategy, referred to as C621, which achieves a data reduction ratio of six to one for the probabilistic component (i.e., the residual picture) in an efficient manner. The findings demonstrated a significant increase in

performance in the context of CR, surpassing the well-recognized standard JPEG by a factor of three. Awad et, al.¹¹ proposed a hybrid color image compression method by utilizes the YCbCr color transformation paradigm based on DWT and DCT. The resulting CR value was found to be roughly 2.5. Ali et al.¹² developed a lossy hybrid compression system that utilized the YCbCr color transformation model for the compression of medical photographs. The system employed a hybrid approach, incorporating both DWT and DCT. Kumar and Kumar¹³ analyzed arithmetic and Huffman compression techniques, utilizing a combination of DWT and DCT, providing valuable insights into the applicability of these methods in color image compression. Elamparuthi¹⁴ contributed to this field by implementing a hybrid color image compression technique that integrates principal component analysis (PCA) and a discrete Tchebichef transform and the results showed CR range from 8 to 11. Ahmad et al.¹⁵, explored image compression for multimedia communication using a hybrid approach of DWT and DCT. Collectively, these studies contribute to the dynamic landscape of color image compression by presenting diverse strategies and methodologies for researchers to consider in their quest for optimal compression techniques. Nandeesh and Somashekar¹⁶ proposed a hybrid

compression method that combines the DWT and block vector quantization (BVQ) and the results showed CR reached to 24.38%. Similarly, Ranjan and Kumar¹⁷ proposed a hybrid system for image

compression that integrates DWT, Canonical Huffman Coding (CHC), and Principal Component Analysis (PCA) to improve CR.

Materials and Methods

Proposed System

In this proposed system a new hybrid model is designed by adaptive and combining four image compression techniques in an efficient way in order

to enhance the compression efficiency. The proposed system comprises four primary stages, whereby each stage involves the execution of a distinct algorithm. See Fig. 1.

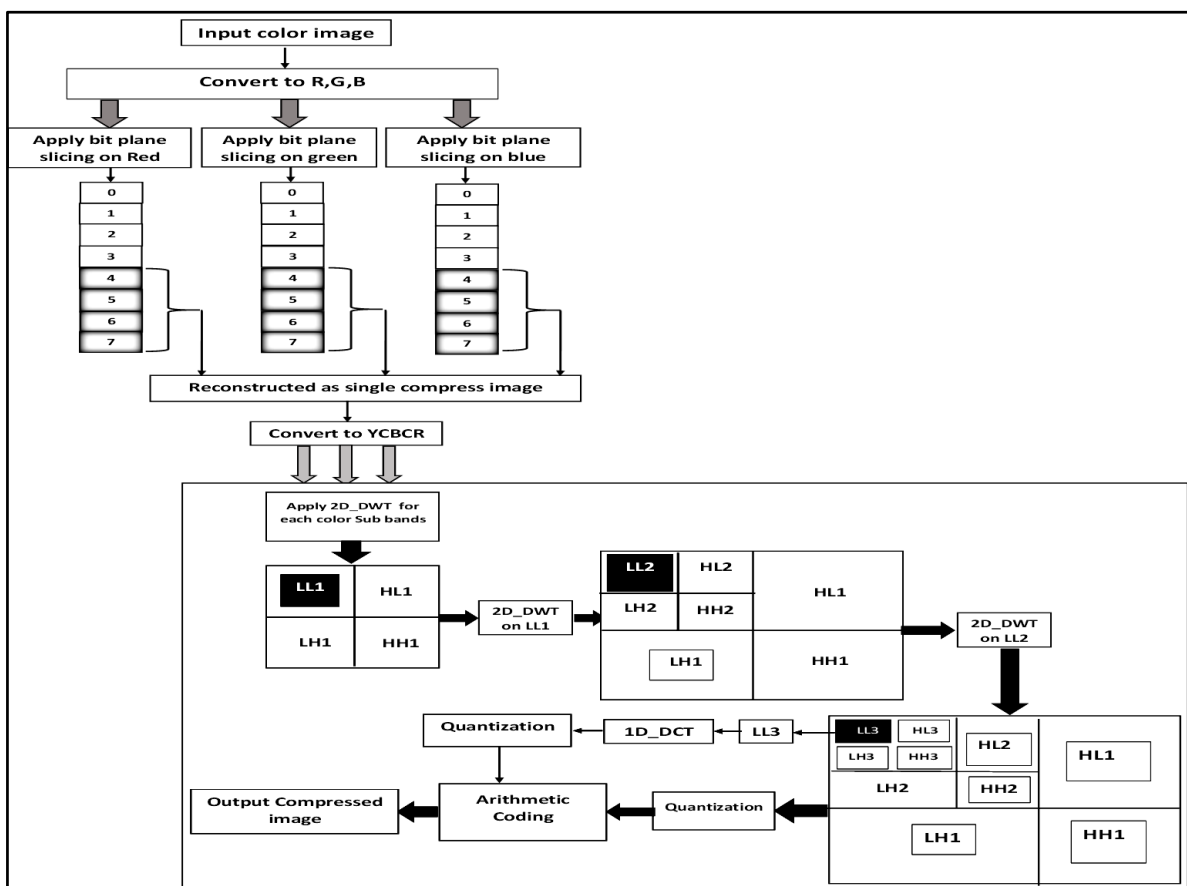


Figure 1. The block structure of the proposed system.

During the initial phase, the bit-plane slicing compression approach is performed on a color image. This process involves separating the image to its color components: red (R), green (G), and blue (B) followed by slicing every color band into 8-bit planes. In this process, the first four-bit plane, also known as the least significant bit (LSB) plane (from 0 to 3 plane), is disregarded, but the most significant bit (MSB) plane (from 4 to 7 plane) is retained for each band because the LSB planes contain the least

images information while the MSB contains the most efficient information about the image. Hence, Ignoring LSB planes will not degrade image quality but will result in smaller file sizes, and then the three color bands are again reconstructed into a single compressed image. The resulting compressed image is then passed on to the subsequent step. In the subsequent phase, the compressed image undergoes a conversion into the YCbCr color space, followed by the application of a three-level DWT on each

individual color space (Y, Cb, and Cr), respectively. That results in two sets of sub bands (HL2, LH2, and HH2) and (LL3, HL3, LH3, and HH3). Subsequently, quantization is applied to all sub bands, excluding the low-frequency sub band (LL3). One-dimensional DCT is applied to LL3, followed by quantization of the resulting DCT coefficient. Finally, the arithmetic coding procedure is employed to compress the image file.

Bit Plane Slicing

It's a lossy compression technique. It a basic image processing method that slices the picture into layers of binary 0s and 1s. The image's bit depth determines the number of layers from plane one to plane N. Pixel intensity is represented by bit depth. In the case of a grayscale image, characterized by a single channel, the bit depth is often set at 8 bits. In this particular scenario, the image is partitioned into 8 distinct layers. The first bit, denoted as LSB of a binary integer, is inefficient and has a very little value (one if this bit = 1). Where the LSB has zero effect on the value of the pixels. The final bit, denoted as the MSB, is highly effective and represents the pixel's weight (which equals 2^{N-1} if this bit = 1)¹⁸. In the case of color image, the image consists mainly of groups of pixels. For instance, a color image of size (256*256) has 256 pixels in the horizontal and vertical direction, and each pixel contains information about the image. The color image is comprised of three color bands, namely red, green, and blue, which means that every band is a matrix with a size of (256*256) and each band is a single grayscale image. The pixel of these bands lies between 0 and 255; the total is 256, and that is equal to 2^8 , where 0 means the pixel is black and 255 means the pixel has color white. The LSB is in bit plane 0, and the MSB can found in bit plane 7. The upper bit-planes involves the most important visual data, whereas the lower bit-planes store the more nuanced data. Only top bit-planes can resemble the original picture. Increased top bit-planes improve picture quality¹⁹. Therefore, for image compression, only the MSB was used to represent the image and the LSB was ignored.

Discrete Cosine Transform (DCT)

DCT is a mathematical technique that transforms a set of data points into a representation consisting of

the summation of cosine functions that occurs at various frequencies²⁰. It is an orthogonal and real transform that makes use of the real sections of the Fourier transform. Since human vision is best at picking up low frequencies, a cryptosystem can safely ignore high frequency elements. The majority of signal information is typically only included in a handful of low-frequency components, so those that aren't as important can be ignored. Because of this trait, the JPEG compression technique is designed to ignore the high frequency content in an image²¹. DCT can be classified into two primary categories: the one-dimensional variety and the two-dimensional variety. The mathematical expression for 2D DCT of an image could be stated as in Eq. 1.

$$D_{DCT}(i, j) = \frac{1}{\sqrt{2n}} B(i) B(j) \sum_{x=0}^{N-1} \sum_{y=0}^{N-1} M(x, y) * \cos\left[\frac{2x+1}{2n} i\pi\right] \cos\left[\frac{2y+1}{2n} j\pi\right] \dots 1$$

Where, $B(u) = \begin{cases} \frac{1}{\sqrt{2}} & \text{if } u = 0 \\ 1 & \text{if } u > 0 \end{cases}$ and $M(x, y)$ is an

image matrix with dimensions x and y .

In case of image compression by using 2DCT, the initial step involves dividing the source image to $8*8$ block size. Subsequently, the DCT coefficients undergo the application of an $8x8$ quantization table. As indicated in Eq. 2, the process of quantization involves dividing every element of the modified original data matrix by the equivalent element in the quantization matrix Q , followed by rounded up the resulting fraction to the nearest integer number.

$$D_{quant}(i, j) = \text{round} \left\{ \frac{D_{dct}(i, j)}{Q(i, j)} \right\} \dots 2$$

After that, a suitable scaling factor is applied, resulting in compressed data. For reconstructed the image, rescaling and de-quantization are used to piece back together the original data and then the inverse DCT is applied to the de-quantized matrix²².

Discrete Wavelet Transform (DWT)

DWT is a wavelet transformation that breaks down a signal into subsets, each of which is a set of coefficients characterizing the signal's development through time at a certain frequency²³. The analysis of an image in DWT involves the utilization of an analysis filter bank in conjunction with a decimation operation. The analysis filter bank is comprised of a set of low-pass and high-pass filters that correspond

to each level of decomposition. The low pass filter is utilized to extract the approximate information contained within an image, while the high pass filter is employed to extract finer details, such as the edges. The 2-dimensional transform is derived by combining two distinct 1-dimensional transforms. In the context of one-dimensional DWT, it is observed that the approximation coefficients primarily encompass low frequency information, while the detail coefficients predominantly encapsulate high frequency information. The utilization of 2D DWT involves the decomposition of the image into four distinct sub bands²⁴.

These sub-bands consist of different frequency features in both diagonal and vertical orientations, which include the low frequency components in both directions (LL), the low frequency in the diagonal orientation and high frequency component in the vertical orientation (LH), the high frequency component in the diagonal orientation and low frequency in the vertical orientation (HL), and the high frequency components in both orientations (HH). Eq. 3 and Eq. 4 give the mathematical expressions that depict the transformation of image (Z) for one and two level of DWT, and its resulting sub-bands, respectively.

$$Z_1 = Z_a^1 + \{Z_h^1 + Z_v^1 + Z_d^1\} \quad \dots 3$$

$$Z_2 = Z_a^2 + \sum_{i=1}^2 \{Z_h^i + Z_v^i + Z_d^i\} \quad \dots 4$$

Where Z_a^1 stands for the input image's approximation (a scaled-down version), Z_h^1 , Z_v^1 and Z_d^1 stand for horizontal, vertical, and diagonal features, and the powers of the terms stand for the depth of decomposition. The LL sub band has the potential to undergo sequential breakdown leading to additional decompositions and ultimately in the image being divided into several bands²⁵.

Arithmetic Coding

Arithmetic encoding is a type of entropy encoding employed in lossless data and image compression²⁶. The fundamental concept underlying arithmetic coding is the allocation of an interval to each symbol. The process involves using a binary numerical system to represent a sequence of symbols. Beginning with the subdivision of a half-open

encoding range [0,1) based on the probabilities associated with the symbols being encoded. The initial symbol that is encoded will be allocated to a specific subdivision. This subdivision then generate a new interval, which will be subdivided similarly for the second symbol. This procedure is repeated until all sequence symbols are encoded²⁷.

Performance Measurement

Three measurement metrics were employed to compute the effectiveness of the proposed system in the context of image compression.

1. Compression Ratio (CR)

This metric measures the effectiveness of the proposed approach under consideration in terms of image compression. A higher ratio means that the image has been compressed efficiently. As seen in Eq. 5, CR is measured by calculating the percentage between the uncompressed and compressed versions of an image is used²⁸.

$$CR = \frac{\text{Original Image Size}}{\text{Compressed Image Size}} \quad \dots 5$$

2. Peak Signal to Noise Ratio (PSNR)

It's a quality metric, which is quantifies the relationship between the peak signal and the ratio of noise (MSE). The larger PSNR value indicates a higher image quality²⁹. As shown in Eq. 6, the PSNR can be calculated for color image³⁰.

$$IMG_{psnr} = 10 \log \frac{255^3 * 3}{img_{MSE}^R + img_{MSE}^G + img_{MSE}^B} \quad \dots 6$$

Where img_{MSE}^R , img_{MSE}^G and img_{MSE}^B is the mean square error of R, G, and B, consecutively. IMG_{MSE} can be calculated as in Eq. 7.

$$IMG_{MSE} = \frac{1}{m*n} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} [X(i,j) - Y(i,j)]^2 \quad \dots 7$$

Where, m and n symbols the image dimensions. X symbols the source image, and Y symbols the decompressed image.

3. Structural Similarity Index (SSIM)

This metric indicates the degree of similarity between the decompression versions of an image to the original. The range of SSIM is between zero and

one. Where, one means the two images are identically matching³¹. SSIM can be calculated as Eq. 8.

$$SSIM(i, j) = [L(i, j)] * [C(i, j)] * [S(i, j)] \dots 8$$

Results and Discussion

To test the effectiveness of the proposed image compression system, the propose algorithm has been performed on MATLAB R2021a running on system with core i7 processor, 8 GB of RAM, and Windows 11 operating system. Eight standard color images are

Where (i) symbol the original image, j symbols Decompression image, L is the luminance, C is contrast, and S is the structure³².

used as test images, which are Lena, Bird, Peppers, Baboons, Car, Flowers, Colors and Wallpaper to ensure the findings of the experiments. As seen in Fig. 2.



Figure 2. The input images used to evaluate the propose algorithm.

Three experiments are performed in this research by using different image sizes, which are (256*256), (512*512), and (1024*1024). In addition, four quantization coefficients are used, where Q1= [0.05, 0.2, 0.2], Q2= [0.1, 0.3, 0.4], Q3= [0.1, 0.2, 0.4], and Q4= [0.2, 0.3, 0.4], each one of these quantization

coefficients consists of three values, each value used to quantize different color space (y, cb, and cr), respectively. See Fig. 3 which shows the output decompressed images obtained from the proposed system.



Figure 3. The output decompressed images.

First Experiments

In this test, the proposed method was performed using eight color images with a size of 256*256 and four quantization coefficients. The compression

result evaluated by using PSNR, SSIM, and CR. See Table 1.

Table 1. The results of the first experiment

Image name	size	quantization	PSNR	SSIM	CR
Lena.bmp	256*256	Q1	27.2841	0.9755	9.6183
		Q2	26.9587	0.9724	12.2857
		Q3	26.9258	0.9719	13.4987
		Q4	26.2473	0.9650	15.7261
Bird.bmp	256*256	Q1	28.0390	0.9127	9.2805
		Q2	27.5905	0.9095	11.8775
		Q3	27.4006	0.9071	12.7800
		Q4	26.6547	0.8973	15.1634
Peppers.bmp	256*256	Q1	28.3594	0.9692	10.6597
		Q2	27.9556	0.9655	13.4442
		Q3	27.8145	0.9640	14.3426
		Q4	27.5749	0.9612	17.1695
Baboon.tiff	256*256	Q1	27.1475	0.8628	11.7189
		Q2	24.2897	0.8627	8.1964
		Q3	24.0527	0.8571	10.1848
		Q4	23.9668	0.8534	11.0349
CarHouse.bmp	256*256	Q1	25.9013	0.9212	9.0732
		Q2	25.3838	0.9076	11.4068
		Q3	25.3363	0.9072	12.3544
		Q4	24.2809	0.8785	14.2263
Flowers.bmp	256*256	Q1	25.4717	0.8982	9.7062
		Q2	25.0213	0.8862	12.3065
		Q3	24.8233	0.8808	13.0645
		Q4	24.1765	0.8568	15.3552
Colors.bmp	256*256	Q1	28.0946	0.9689	10.4880
		Q2	27.8502	0.9659	13.2646
		Q3	27.7072	0.9634	14.1496
		Q4	27.3056	0.9570	16.6518
Wallpaper.jpg	256*256	Q1	27.7302	0.9389	13.0083
		Q2	27.4119	0.9329	16.5900
		Q3	27.3569	0.9332	17.7877
		Q4	26.9045	0.9247	20.7568

Second Experiment

In this test, the proposed method is performed using eight standard images with a size of 512*512 and

four quantization coefficients. The compression result is evaluated using PSNR, SSIM, and CR. As seen in the Table 2.

Table 2. The results of the second experiment

Image name	Size	Quantization	PSNR	SSIM	CR
Lena.bmp	512*512	Q1	28.0694	0.9800	14.3045
		Q2	27.8002	0.9774	19.5183
		Q3	27.8039	0.9774	22.1125
		Q4	27.2625	0.9724	26.1725
Bird.bmp	512*512	Q1	29.2498	0.9059	16.7536
		Q2	28.9515	0.9043	22.9716
		Q3	28.8917	0.9040	25.6601
		Q4	28.2058	0.8965	31.2138
Baboon.tiff	512*512	Q1	22.6298	0.8296	11.6784
		Q2	22.4107	0.8214	15.3268
		Q3	22.3256	0.8171	16.9227

Peppers.bmp	512*512	Q4	21.9470	0.8002	20.9458
		Q1	29.0870	0.9705	16.7740
		Q2	28.8965	0.9698	22.2458
		Q3	28.8510	0.9698	24.8070
CarHouse.bmp	512*512	Q4	28.6561	0.9681	31.0806
		Q1	26.7275	0.9254	14.9254
		Q2	26.1561	0.9117	19.7571
		Q3	26.0899	0.9110	21.9404
Flowers.bmp	512*512	Q4	25.1463	0.8885	26.6235
		Q1	27.3387	0.9158	16.0785
		Q2	26.7184	0.9004	21.9870
		Q3	26.5462	0.8967	23.4022
Colors.bmp	512*512	Q4	25.6192	0.8679	28.9897
		Q1	28.4856	0.9704	18.0914
		Q2	28.3961	0.9696	23.8262
		Q3	28.3526	0.9688	25.8610
Wallpaper.jpg	512*512	Q4	28.0540	0.9643	31.6969
		Q1	28.4050	0.9399	23.4826
		Q2	28.0763	0.9334	30.6948
		Q3	28.0656	0.9344	34.5426
		Q4	27.5042	0.9239	41.0262

Third Experiment

In this test, the proposed method was performed by using eight standard color images with a size of

1024 x 1024 and four quantization coefficients. The compression result is evaluated by using PSNR, SSIM, and CR. As seen in Table 3.

Table 3. The results of the third experiment

Image name	Size	Quantization	PSNR	SSIM	CR
Lena.bmp	1024*1024	Q1	27.9183	0.9769	16.9297
		Q2	27.0700	0.9677	24.2720
		Q3	27.0677	0.9677	27.8600
		Q4	26.9252	0.9666	35.7554
Bird.bmp	1024*1024	Q1	29.3061	0.9005	19.0247
		Q2	29.1581	0.8966	27.1645
		Q3	29.1662	0.8924	27.7923
		Q4	28.8579	0.8929	35.7433
Bapoon.bmp	1024*1024	Q1	25.2095	0.8810	12.8630
		Q2	23.7533	0.8314	17.2431
		Q3	23.6843	0.8280	19.1690
		Q4	21.6179	0.7366	23.6772
Peppers.bmp	1024*1024	Q1	28.7963	0.9599	21.0827
		Q2	28.7799	0.9607	30.5277
		Q3	28.7820	0.9611	35.3421
		Q4	28.8106	0.9627	44.7364
CarHouse.bmp	1024*1024	Q1	25.6291	0.8595	25.1797
		Q2	25.5037	0.8671	34.5267
		Q3	25.5334	0.8709	38.2325
		Q4	25.1184	0.8641	48.8831

Flowers.bmp	1024*1024	Q1	26.9820	0.8695	20.8948
		Q2	26.7711	0.8680	30.1093
		Q3	26.7419	0.8685	33.4980
		Q4	26.3497	0.8597	42.7856
Colors.bmp	1024*1024	Q1	28.3462	0.9631	20.8069
		Q2	28.3185	0.9627	28.4272
		Q3	28.3471	0.9635	31.6800
		Q4	28.2502	0.9621	39.6192
Wallpaper.jpg	1024*1024	Q1	27.0347	0.9136	29.9816
		Q2	26.9682	0.9122	43.7807
		Q3	27.0096	0.9136	49.8689
		Q4	26.9325	0.9033	62.5033

Comparison between the proposed system and jpeg

In this experiment, the proposed system compares with standard image compression technique of JPEG XnView software. The comparison applied by using 8 color images with various sizes in kilobytes where

(1kb = 1024 bytes). The comparison applied between the two methods in terms of CR measure. The result clearly indicated that the proposed system demonstrated a higher level of efficacy in comparison to standard JPEG approach. Table 5 shows the comparison results between the proposed system and the standard JPEG.

Table 5. The comparison results between proposed system and JPEG

Image Name	Image Size (kb)	Proposed System		JPEG	
		Size (kb)	CR	Size (kb)	CR
Baboon.tiff	192	14.7764	12.9937	27.6621	6.9409
Bird.bmp	192	12.6621	15.1634	24.2861	7.9057
CarHouse.bmp	768	28.8467	26.6235	61.0576	12.5783
Colors.bmp	768	24.2295	31.6969	45.8174	16.7622
Lina.bmp	3072	85.9170	35.7554	205.5508	14.9452
Peppers.bmp	3072	68.6689	44.7364	131.0898	23.4343
Flowers.bmp	3072	71.7998	42.7856	155.7363	19.7256
Wallpaper.jpg	3072	49.1494	62.5033	86.0537	35.6986

Conclusion

In this research, a new hybrid system for image compression is proposed by combining the benefits of four techniques: bit plane slicing, DWT, DCT, and Arithmetic coding. Throughout this research, three experiments have been implemented to analyze the performance of the proposed hybrid system. The experiments have been implemented on color images with sizes (256*256), (512*512), and (1024*1024). By comparing the findings of the three experimental, it can be seen that:

1. Increasing the image size from 256 to 1024 affects the compression efficiency, as when using an image with a size of 1024, a higher CR was obtained compared to when using an image with a size of 256.
2. Choosing the value of quantization affects the compression ratio, as a higher compression ratio was obtained when using Q4 and Q3. While Q2 gave a moderate compression ratio and resolution, and using Q1 had the lowest value in compression ratio but with higher image resolution.
3. Implementing the third experiment led to a higher CR compared to the first and second experiments, where the compression ratio reached 62%.
4. The best image quality and similarity were achieved by using quantization (Q1 and Q2) depending on PSNR and SSIM values.

5. The best image compression was achieved by using quantization (Q3 and Q4) depending on CR value.
6. Increasing the image size and choosing the appropriate quantization value accurately can improve the effectiveness of the suggested system in image compression.
7. The suggested system provides a balance between obtaining a high CR while maintaining an acceptable image similarity and quality ratio, which makes it a promising system for future applications.
8. In comparison between the proposed system and jpeg, the suggested system provides higher compression effectiveness compared to jpeg, as the CR when using jpeg reached 35%, while the suggested system provided a CR of 62%.

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Authors' Declaration

- Conflicts of Interest: None.
- We hereby confirm that all the Figures and Tables in the manuscript are ours. Furthermore, any Figures and images, that are not ours, have been included with the necessary permission for re-publication, which is attached to the manuscript.
- No animal studies are present in the manuscript.
- No human studies are present in the manuscript.
- Ethical Clearance: The project was approved by the local ethical committee at Altınbaş University.

Authors' Contribution Statement

In this research, H.K.K and A.K.T. both made significant contributions. H.K.K. took the lead in designing and implementing the proposed system for the color image compression. They also played a key role in writing the manuscript, ensuring clarity and

coherence. Meanwhile, A.K.T. contributed by providing guidance and expertise throughout the research. Together, H.K.K and A.K.T. thoroughly examined and verified the results, ensuring the accuracy and validity of the research results.

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نظام فقدان متكيف لضغط الصور الملونة بالاعتماد على خوارزمية هجينة

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الخلاصة

مع التطور الحاصل في العصر الرقمي، أصبحت تقنيات الوسائط المتعددة منتشرة، حيث يتوقع المستخدمون محتوى صوتي ومرئي وصوري عالي الجودة عبر مختلف المنصات والأجهزة الرقمية. ونتيجة لذلك، زاد حجم البيانات الناتجة عن برامج الوسائط المتعددة هذه بشكل كبير. بالإضافة إلى ذلك، أدى النمو الهائل في استخدام الوسائط المتعددة إلى زيادة في عدد الصور التي يتم استخدامها وإنشاؤها، مما خلق تحديات من حيث الحاجة إلى زيادة في سعة التخزين وتحسين سرعة نقل البيانات. ومن أجل مواجهة هذه التحديات، برز ضغط الصور كحل بالغ في الأهمية. حيث يعمل ضغط الصور من خلال تقليل حجم الصورة دون المساس بشكل كبير إلى جودتها. ومع التقدم التكنولوجي الحاصل بشكل كبير، ستصبح الحاجة إلى المزيد من تقنيات ضغط الصور أمر في بالغ الأهمية. تقدم هذه الورقة البحثية نظام ضياع هجين لضغط الصور باستخدام أربع تقنيات ضغط مهجنة وهي تقطيع مستوى البيت، وتحويل المويجه المتقطع (DWT)، وتحويل جيب التمام المتقطع (DCT)، والتشفير الحسابي. ولذلك لتنفيذ هذه الطريقة المقترحة في هذا البحث، تم إجراء ثلاث تجارب باستخدام صور ذات أبعاد حجمية مختلفة وهي (256*256) و (512*512) و (1024*1024) وأربعة من معاملات التكميم المختلفة. ومن أجل قياس كفاءة النظام المقترح تم استخدام ثلاثة مقاييس مختلفة وهي: نسبة ذروة الإشارة إلى نسبة الضوضاء (PSNR)، ومؤشر التشابه الهيكلية (SSIM)، ونسبة الضغط (CR). وقد أظهرت النتائج إن النظام المقترح نجح في رفع نسبة ضغط الصور إلى مستوى أعلى عند مقارنته بتقنية JPEG القياسية حيث وصلت نسبة الضغط CR عند استخدام JPEG إلى 35%، بينما قدم النظام المقترح نسبة ضغط أعلى قد وصلت إلى 62% مع الحفاظ على مستوى مرضي من جودة الصورة.

الكلمات المفتاحية: التشفير الحسابي، تقطيع مستوى البيت، نسبة الضغط، تحويل جيب التمام المتقطع، تحويل المويجه المتقطع، ضغط الصور، نسبة الضغط إلى الضوضاء، مؤشر التشابه الهيكلية.