



ISSN: 0067-2904

Image Compression Based on Arithmetic Coding Algorithm

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Received: 4/1/2020

Accepted: 15/3/2020

Abstract

The past years have seen a rapid development in the area of image compression techniques, mainly due to the need of fast and efficient techniques for storage and transmission of data among individuals. Compression is the process of representing the data in a compact form rather than in its original or incompact form. In this paper, integer implementation of Arithmetic Coding (AC) and Discreet Cosine Transform (DCT) were applied to colored images. The DCT was applied using the YCbCr color model. The transformed image was then quantized with the standard quantization tables for luminance and chrominance. The quantized coefficients were scanned by zigzag scan and the output was encoded using AC. The results showed a decent compression ratio with high image quality.

Keywords: lossy compression, Image compression, Arithmetic coding, Discreet Cosine Transform, and YCbCr.

ضغط الصور باستخدام خوارزمية الترميز الرياضي

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الخلاصة

شهدت السنوات الأخيرة تطوراً سريعاً في مجال تقنيات ضغط الصور وهذا يرجع بشكل أساسي إلى الحاجة إلى تقنيات سريعة وفعالة لتخزين ونقل البيانات بين الأفراد. يمثل الضغط البيانات في نموذج موجز وليس في شكله الأصلي أو غير المضغوط. في هذا البحث، يتم تطبيق الترميز الرياضي (AC) وتحويل جيب التمام (DCT) على الصور الملونة. يتم تطبيق تحويل الجيب تمام على الصور الملونة في نموذج ألوان YCbCr، ثم يتم قياس الصورة المحولة بجدول الكمي القياسية للإضاءة والتلون. يتم فحص المعاملات الكمية بواسطة المسح متعرج (zigzag) ويتم ترميز المخرجات باستخدام الترميز الرياضي. تظهر النتائج جودة نسبة الضغط وجودة دقة الصور.

1. Introduction

Data compression is utilized to limit the amount of data used to format an image, video, sound, or file content without intense reduction in the resolution of the original data. Image compression is the application of data compression on digital images to lessen the amount of data required to represent a digital image, by lowering the redundancy and irrelevancy of data that format the image, to be able to transmit or save the image in an efficient representation [1, 2].

Image compressions may be either lossless or lossy. In a lossless compression, the original image is identical to the reconstructed one. No information is lost during the compression and decompression stages. Lossless compression is selected to be used for certain critical applications in fields such as

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military uses, space programmes, medicine, or remote-sensing, where keeping all the information is a priority, at the expense of compression. [3]

In lossy compression, the coding process makes certain approximations or quantization in order to better compact the information. Although better compression ratios are achieved, the trade-off is in a reconstructed image which is not identical to the original image in the sense of individual pixel values. However, the information presented may still appear to be visually identical, which is the key to achieve higher compression ratios in lossy compression techniques. It is used in natural images such as those employed in applications where minimum loss of data is acceptable [4, 5]. There are a many techniques utilized for the two types of compression. Arithmetic coding is a sort of entropy encoding that is used in lossless data compression. It is a data compression approach that can encode data (character, image, etc) via creating a code which, in floating point implementation, represents a fraction within the unit interval $[0, 1)$. The algorithm is recursive and, at every recursion, it successively partitions subintervals of the unit interval $[0, 1]$. This implies that, in AC, rather than using a sequence of bits to represent an image, a subinterval of the unit interval $[0, 1)$ is used to represent that symbol. In different words, the data is encoded into a number inside the unit interval $[0, 1)$. However, in integer implementation of arithmetic coding, the initial range $[0, 1)$ can be replaced by $[0, \text{MAX-VALUE})$, where MAX-VALUE is the largest integer number that a computer can handle [6]. Arithmetic coding is a very efficient technique for lossless data compression and it produces a rate, which approaches the entropy of the encoded information [7]. In this paper, integer AC and DCT are applied to colored images. The DCT is applied to colored images in YCbCr color model and the transformed image is then quantized with the standard quantization tables for luminance and chrominance. The quantized coefficients are scanned by zigzag scan and the output is encoded using AC. The results showed a decent compression ratio with high image quality.

Related work

Many image compression schemes have been proposed. In Bilal [8] research, images were processed as three-color channel (red, green, blue). Each channel was distributed into (8×8) blocks of pixels and DCT was performed on each block. These blocks were then quantized and rearranged into 1D array using zigzag scanning, then shift coding was applied to every block to obtain a stream of bits in a binary file. The obtained bit rates were extended to be within specific values of range (11.4, 2.6) and compression ratio (2.76, 13.34). The values of the fidelity parameter, i.e. peak signal-to-noise ratio (PSNR), were within the range of 31.61, 46.21 for Lena test image with sizes of 128×128 and 256×256 , respectively. Anandan and Sabeenian [9] described a method for the compression of numerous medical images using fast discrete Curvelet transform based on wrapping technique. The transformed coefficients were quantized using vector quantization and encoded by using AC. The system was examined on various medical images and the results demonstrated significant improvement in overall performance parameters, such as PSNR and Compression Ratio (CR). Vaishnav *et al.* [10] applied dual-tree wavelet transform and AC methods on medical image (brain MRI images). The dual-tree complex wavelet transform (CWT) was first applied to the images and the transformed coefficients were encoded with AC. The average PSNR value received was 65.30 with an MSE of 27.24. Masmoudi and Masmoudi [11] used AC on a gray image (512×512) that is dividing into non overlapping blocks. The encoder scanned the image in a raster scan order, pixel by pixel and block by block, from left to right and top to bottom. A statistical model was employed which gives possibilities for the entire source symbols to be encoded, by estimating the probability distribution of every block and exploiting the high correlation between neighboring image blocks. Therefore, the probability distribution of every block of pixels was estimated by minimizing the Kullback–Leibler distance between the exact probability distribution of that block and the probability distributions of its neighboring blocks in a causal order. The results showed a lossless compression with a reduction in bit rate by 15.5% to 16.4%. Phyto and Hitwe [12] used floating point implementation of AC with DCT transformation. First, an RGB image was converted to YCbCr color space and then transformed using DCT. The results of transformation were quantized using different quality factors. Then, the quantized output was encoded with floating point AC.

2. Materials and Methods

The steps below explain the proposed system and are shown by figure 1.

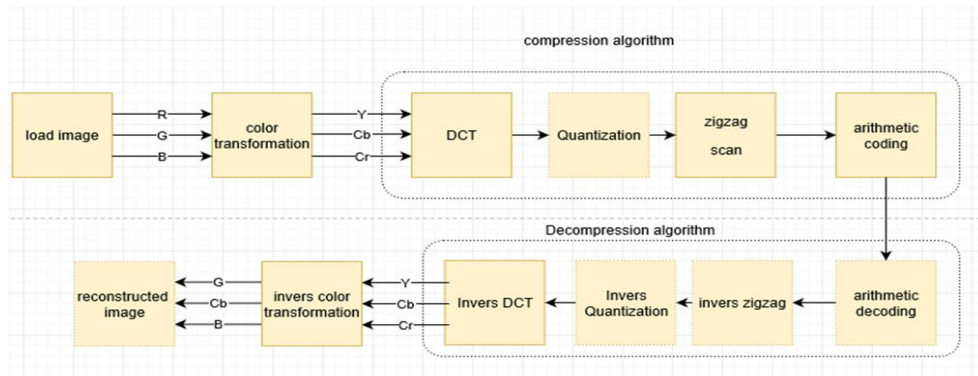


Figure 1-Flow chart diagram of the compression unit of DCT.

Step1: Loading the input non compressed colored image of a size N×N.

Step2: Converting the color space of the input image to YCbCr color model according to equation (1) [11].

$$\begin{bmatrix} Y \\ Cb \\ Cr \end{bmatrix} = \begin{bmatrix} 16 \\ 128 \\ 128 \end{bmatrix} + \begin{bmatrix} 65.481 & 128.553 & 24.966 \\ -37.797 & -74.203 & 112.000 \\ 112.000 & -93.786 & -18.214 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad (1)$$

Step 3: Applying DCT to each color channel according to equation (2) [11]

$$c(u, v) = D(u)D(v) \sum_{x=0}^{N-1} \sum_{y=0}^{N-1} f(x, y) \cos [(2x + 1)u\pi/2N] \cos [(2y + 1)v\pi/2N] \quad (2)$$

$$\text{where } N = 8 \text{ and } c(k) = \begin{cases} \frac{1}{\sqrt{2}}, & \text{for } k = 0 \\ 1, & \text{otherwise} \end{cases}$$

Step 4: Applying quantization using standard quantization tables shown in figure-2 according to equation (3) [11]

Luminance Quantization Table								Chrominance Quantization Table							
16	11	10	16	24	40	51	61	17	18	24	47	99	99	99	99
12	12	14	19	26	58	60	55	18	21	26	66	99	99	99	99
14	13	16	24	40	57	69	56	24	26	56	99	99	99	99	99
14	17	22	29	51	87	80	62	47	66	99	99	99	99	99	99
18	22	37	56	68	109	103	77	99	99	99	99	99	99	99	99
24	35	55	64	81	104	113	92	99	99	99	99	99	99	99	99
49	64	78	87	103	121	120	101	99	99	99	99	99	99	99	99
72	92	95	98	112	100	103	99	99	99	99	99	99	99	99	99

Figure 2-Luminance and chrominance quantization tables.

$$\text{Quantize}(F(x, y)) = \text{Round}\left(\frac{f(x, y)}{p}\right) \quad (3)$$

where f(x, y) is the value to be quantized and p is the corresponding value in the quantization table.

Step 5: Scanning each 8×8 quantized block of DCT using zigzag scan to specify the most important coefficients which require less redundancy. The zigzag operation is shown in figure 3.

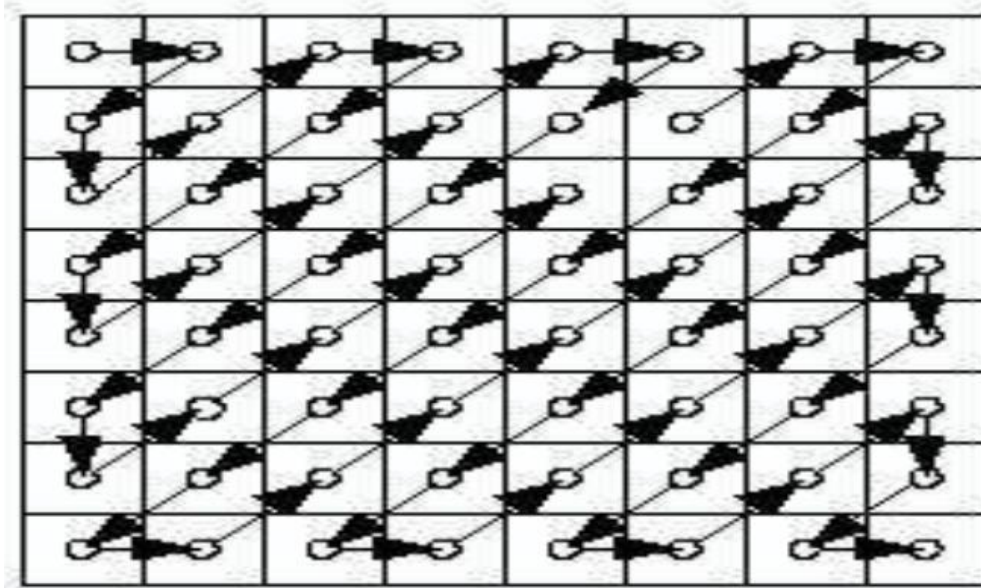


Figure 3-Zig-zag basic operation

Step 6: Starting AC by counting cumulative probabilities for each quantized pixel value according to equation (4) [12]

$$\text{Cum-Count}(i) = \sum_{k=1}^i N_k \tag{4}$$

Step 7: Setting the initial range of the interval to $[0, \text{MAX-VALUE})$, where MAX-VALUE is the largest integer number that a computer can handle. For a 16-bit integer, $\text{MAX-VALUE} = 2^{16} - 1 = 65535$ and hence the initial range will be $[0, 2^{16} - 1)$ [13]; this value depends on the computer used.

Step 8: Updating the Lower (L) and Upper (U) ranges of the interval according to equations (5) and (6) [12]

$$L^{(n)} = L^{(n-1)} + \left\lfloor \frac{(U^{(n-1)} - L^{(n-1)} + 1) \times \text{cum_count}(x_{n-1})}{\text{total_count}} \right\rfloor \tag{5}$$

$$U^{(n)} = U^{(n-1)} + \left\lfloor \frac{(U^{(n-1)} - L^{(n-1)} + 1) \times \text{cum_count}(x_n)}{\text{total_count}} \right\rfloor - 1 \tag{6}$$

Step 9: If the Most Significant Bit (MSB) values of L and U are equal, then send that bit to the coding file, shift L to the left by 1 bit and shift 0 into LSB, shift U to the left by 1 bit, and shift 1 into a Least Significant Bit (LSB).

3. Results and Discussion

The proposed system was tested on 512×512 colored BMP images (figure-4) and compared to the results of applying AC on colored and gray images. Comparison with applying AC was made after dividing the image into 64×64 non overlapping blocks.

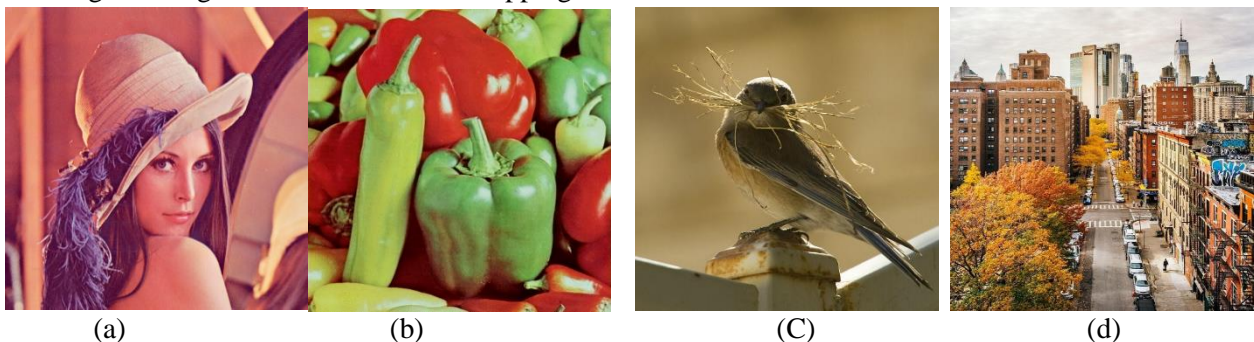


Figure 4-Test images of size 512x512. a) Lena.bmp, b) Peppers_color.bmp, c) Bird.bmp, d) YNC.bmp

The experimental results of the compression process are demonstrated in Table-1 below:

Table 1-The compression performance for the tested images

Tested Images	AC on gray images		AC on Colored images				AC & DCT on Colored			
	CR		CR				CR %	MSE	PSNR	Time sec.
	Full size	64x64	Full size	Time sec.	64x64	Time sec.				
Lena.bmp	3.21	3.53	4.42	133.13	5.24	39.32	23.87	5.3257	41.0485	10.61
peppers_color.bmp	3.93	4.62	3.93	79.89	5.17	38.10	20.74	8.1164	39.0858	10.02
bird.bmp	3.4951	3.61	6.68	161.82	10.96	18.1	30.13	2.1834	44.7806	8.32
NYC.bmp	3.06	3.08	4.39	115	5.28	40.9	19.82	12.9064	37.0577	11.42

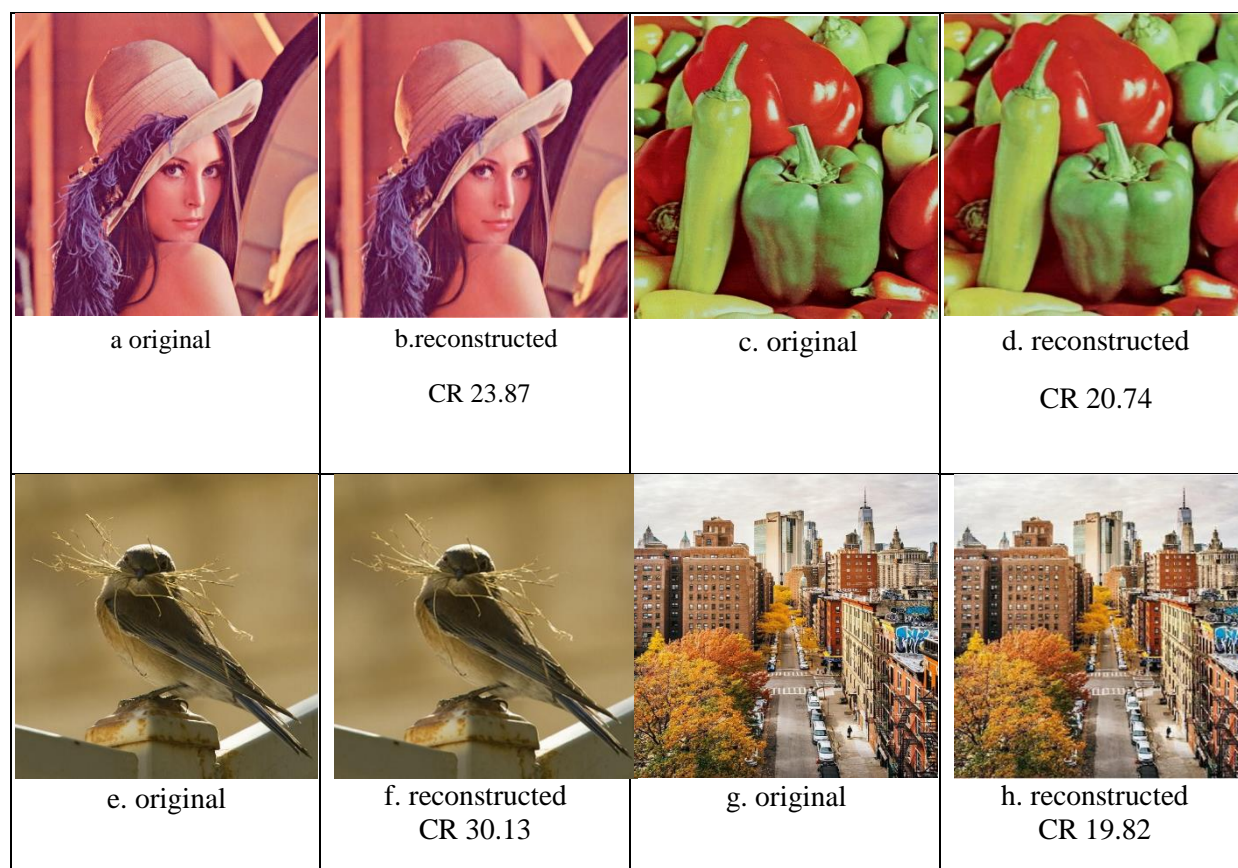


Figure 5- original and reconstructed test images.

The table shows that along time is required to implement AC with no transformation, since the algorithm reads the entire image and counts the probability for every single pixel value. Although the results are lossless, the compression ratio is low. The best performance was obtained using AC with DCT. This is due to the discard of less important frequencies through the quantization step. Figure 5 shows the original and the reconstructed images after the decompression stage.

The applied efficiency parameters are:

- **Mean Square Error (MSE)**

MSE is a function of loss that measures differences between the required response and the actual output of the system, according to equation (7) [12]:

$$MSE = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} [I(x, y) - K(x, y)]^2 \tag{7}$$

where m and n are the size values of the input image $I(i, j)$, while $K(i, j)$ is the recovered image.

- **Peak Signal to Noise Ratio (PSNR)**

PSNR is the ratio between the maximum signal power and the corrupting noise power [13]. It is denoted by equation (8) [1].

$$PSNR = 10 \cdot \log_{10} \left(\frac{MAX_i^2}{MSE} \right) \quad (8)$$

where MAX_i is the possible maximum value of pixels of an image.

- **Compression Ratio (CR)**

The CR refers to the size of the original images divided by the size of the compressed images [12], as denoted by equation (9).

$$CR = \frac{\text{original size}}{\text{compressed size}} \quad (9)$$

4. Conclusions

This paper aims to apply arithmetic coding on colored images and gain a decent compression ratio. A compression scheme that includes using RGB to YCbCr color conversion, DCT, quantization using quantization table, zigzag scan, and integer arithmetic coding was proposed. Testing results and analysis of the proposed system indicates that dividing an image into blocks increases the compression ratio by 1.14%, whereas using the DCT increases the ratio by 5.5%. Also, using DCT with zig-zag scan speeds up the compression process time. The proposed algorithm, implemented using MATLAB, is easy to run. A future work may include additional transforms, such as wavelet transform or Walsh-Hadamard transform to gain higher compression ratio.

References

1. Dhawa. S. **2011**. A Review of Image Compression and Compression of its Algorithm. India, *International journal of electronic and communication technology*, **2**(1): 22-26.
2. Ahmed. S. D. **2016**. *Image compression using Adaptive Polynomial Transform*. MS.c. thesis, collage of science, Baghdad University, Iraq.
3. Ziv, J. and Lempel, A. **1977**. A Universal Algorithm for Sequential Data Compression. *IEEE Trans. on Information Theory*, **23**(3): 337-343.
4. Kaushik. A. and Nain. D. **2014**. Image compression algorithm Using DCT. *Journal of Engineering Research and Applications*, **4**(4): 357-364.
5. Tajne. A. S. and Kulkarni. P. S. **2015**. A survey on Medical Image compression Using Hybrid Technique. *International journal of computer Science and mobile computing*, **4**(2): 18-23.
6. Rabbani. M and Jones, P. **1991**. *Digital image compression techniques*. Washington. The International Society for Optical Engineering.
7. Sayood.K. **2006**. *“Introduction to Data Compression”*. 3rd edition. San Francisco. Elsevier.
8. Ahmed. B. K. **2011**. DCT Image Compression by Run-Length and Shift Coding Techniques. *J. of university of Anbar for pure science*, **5**(3): 39-44.
9. Anandan. P and Sabeenian. R. S. **2016**. Medical Image Compression Using Wrapping Based Fast Discrete Curvelet Transform and Arithmetic Coding. *Circuits and Systems*, **7**: 2059-2069.
10. Vaishnav. M., Kamargaonkar. C. and Sharma. M. **2017**. Medical Image Compression Using Dual Tree Complex Wavelet Transform and Arithmetic Coding Technique. *International Journal of Scientific Research in Computer Science, Engineering and Information Technology*, **2**(3): 172-176.
11. Masmoudi. A. and Masmoudi. A. **2015**. A New Arithmetic coding Model for a Block Based Lossless Image Compression based on Exploiting Inter Block Correlation. *Springer*, **9**(5): 1021–1027.
12. Phyto. E. and Htwe. N.A. **2014**. DCT Based Image Compression using Arithmetic Encoding Technique. *International journal of scientific engineering and technology research*, **3**(14): 3025-3030.
13. Salomon. D, Motta. G, **2009**. *Hand Book of Data Compression*. 5th edition. London. Springer.