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A PERFORMANCE STUDY OF TWO JPEG COMPRESSION APPROACHES

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ABSTRACT

As technology continues to advance, and the transition into the digital age, we find ourselves dealing with an ever-expanding volume of information, often leading to challenges in management. Consequently, there is a growing need to store and retrieve digital information in a manner that is both efficient and effective. This paper discusses jpeg image compression techniques; and presents a comparison between two modifications of jpeg image compression techniques. Both of two modifications rely on applying DCT to the divided blocks of the image. They differ in the way of selecting the coefficients resulted from DCT to be quantized in order to remove redundancy. The quality of the compressed images is evaluated using Peak Signal to Noise Ratio (PSNR), Weighted Peak Signal to Noise Ratio (WPSNR) and spatial frequency measurement (SFM).

Keywords: jpeg compression, SFM, WPSNR, SSIM.

1. INTRODUCTION

With each passing day, computers are becoming increasingly powerful, leading to a surge in the utilization of digital images. However, this widespread use of digital images brings about a significant challenge managing the substantial volume of data these images represent. The storage and transmission of uncompressed multimedia data, encompassing graphics, audio, and video, pose considerable demands on storage capacity and bandwidth, highlighting a pressing issue in the digital landscape. Reducing the bandwidth needs of any given device will result in significant cost reductions and will make use of the device more affordable.

Image compression plays a significant role in the realm of image information processing. The dimensions of image data hold paramount importance during image processing as they can impact various aspects, including design architecture, memory requirements, processing time for large datasets, and overall processing complexity. In the work [10] K. Dharavath and S. Bhukya introduce a novel method for compressing images while maintaining their essential features intact. Recent research such as work in [11] aims to Identify Image Modifications using DCT and JPEG Quantization Technique. in [12] the authors propose a new approach which uses the features of three methods: Discrete HAAR Wavelet Transform (DHWT), the Singular Value Decomposition (SVD) and Joint Photographic Experts group (JPEG). In [14]-[15] the authors present A Review of different image Compression Techniques. In the work [16] Hussain, A, Al-Fayadh, A and Radi, N introduce Image Compression Techniques: A Survey in Lossless and Lossy algorithms. Indeed, they begin by compressing the image by deleting some value from the input image.

Data compression offers ways to represent data in a more compact way, so that one can store more data and transmit it faster. The advantages of data compression come at the expense of numerical computations, and therefore we can trade off computations for storage or bandwidth. Before storing or transmitting data we process it in such a way that will require fewer bits for its representation [2]. One of the most popular and comprehensive still farm compression is the jpeg (for joint photographic expert group) standard in the baseline coding system, which is based on discrete cosine transform [3] and is adequate for most compression applications.

This paper is organized as follows: Section II explains the principles of compression. Section III presents the proposed algorithm. IV briefly explains the performance evaluation criteria. Section V introduces the experimental results and section VI gives the concluding remarks.

2. PRINCIPLES BEHIND COMPRESSION

Recently, most of the proposed localization schemes are based on RSSI technique but the RSSI signal propagation models easily suffer from outer uncertain influences, such as signal fading, non-uniform spreading, and reflections. An RSSI-based approach therefore needs more data than other methods to achieve higher accuracy. Data compression techniques exploit inherent redundancy and irrelevancy by transforming a data file into a smaller file from which the original image file can later be reconstructed, exactly or approximately [1].

Redundancy reduction focuses on eliminating duplications present in the signal source, such as image or video data. Irrelevancy reduction, on the other hand, involves discarding portions of the signal that are unlikely to be perceptible to the signal receiver, specifically the Human Visual System (HVS). In general, there are four types of redundancy can be summarized:

- Spatial Redundancy due to correlation between neighboring pixels.
- Spectral redundancy arises from the correlation between distinct color planes or spectral bands.
- Temporal redundancy due to correlation between adjacent frames in a sequence of images (in video applications).
- Statistical Redundancy due to statistical properties of images.

Image compression research aims at reducing the number of bits needed to represent an image by removing the spatial and statistical redundancies as much as possible [15]. The volume of data required describing such images greatly slow transmission and makes storage prohibitively costly. The information contained in images must, therefore, be compressed by extracting only visible elements, which are then encoded [14].

The volume of data is significantly diminished through this process. The primary objective of image compression is to decrease the bit rate for transmission or storage while preserving an acceptable level of fidelity or image quality. Compression can be broadly categorized in two ways:

- Lossless Compression: This method compresses data in a way that allows for complete reconstruction (uncompressing) without any loss of detail or information [16].
- Lossy Compression: In contrast, lossy compression does not maintain the exact pixel-to-pixel representation of the original image. Instead, it capitalizes on the limitations of the human eye to approximate the image in a way that appears visually identical to the original. While lossy methods can achieve significantly higher compression rates than lossless methods, they need to be employed judiciously to avoid noticeable degradation in image quality Processing Steps for jpeg Image Compression [17].

3. PROCESSING STEPS FOR JPEG IMAGE COMPRESSION

3.1 JPEG Encoder

The encoding process is started by dividing image data into square blocks and applying DCT show in figure 1. The resultant coefficients are selected and quantized using two approaches [3]-[4].

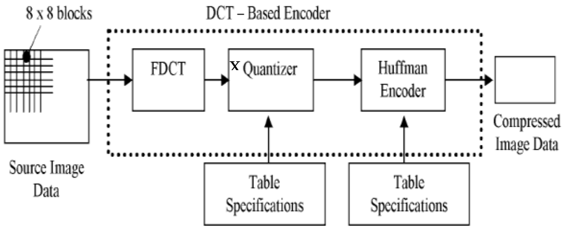


Figure:1 DCT-Based JPEG Encoder Processing Steps

Step1: The image is divided into non overlapping 8*x*8 blocks of pixels start from left to right, top to bottom.

Step2: Every pixel in the block is shifted from an unsigned integer with range $[0, 2^{p}-1]$ to a signed integer with range $[-(2^{p-1}), 2^{p-1}-1]$ by subtracting 2^{p-1} from the value where p is the number of bits per channel (or bits per value). In the case of the standard 8-bit channel the numbers are shifted from [0, 255] to [−128.127] by subtracting 128.Beacause DCT is designed to work in this range.

Step3: Each shifted pixel in the 8x8 block is then transformed into frequency domain via discrete cosine transform (DCT). The transformed 8x8 block now consists of 64 DCT coefficients. The first coefficient (0, 0) is the DC component in the block and the other 63 coefficients are AC component of the block

Step4: The resultant transformed coefficients are then passed to the quantizer which simply reduces the number of bits needed to store the transformed coefficients by reducing the precision of these values. Instead of passing all coefficients to the quantizer, only some selected coefficients (*x*) will be utilized. Two approaches for selection will be adopted.

- 1st approach: after sorting coefficients in all blocks, only the top *k* largest coefficients in magnitude will be kept and the other coefficients will be set to zeros.
- 2nd approach: instead of applying the sorting globally, coefficients of in each block will be sorted locally in decreasing order and only the top *(k/c)* largest coefficients in magnitude will be kept where *c* denotes the number of blocks. This process will be repeated for all blocks.

Step 5: The selected coefficients will be passed through the quantizer. Each of the 64 DCT coefficient F(u,v) is quantized using the stander quantization matrix Q(u,v) by dividing the each coefficient by the corresponding quantize element in the quantization matrix and rounded to the nearest integer as

$$F_q(u,v) = Round(\frac{F(u,v)}{Q(u,v)}) \qquad (1)$$

Quality of the reconstructed image can be controlled by a user by selecting a quality level. The value of quality level may vary from 1 to 100 if another level of quality is desired. It is permissible to use scalar multiples of the JPEG standard quantization matrix. For quality<50 (more compression, lower image quality), the standard quantization matrix is multiplied by 50/quality level and for quality level>50 (less compression, more image quality), the standard quantization matrix is multiplied by (100-quality level)/ 50.

Step 6: After quantization of the DCT coefficients the quantized DC-coefficients are treated differently than the quantized AC-coefficients. The processing order of all coefficients is specified by the zig-zag sequence shown in Figure 2. The differences between successive DC-coefficients are very small values. Thus, each DC-coefficient is encoded by subtracting the DC-coefficient of the previous data unit, as shown in Figure 3, and subsequently using only the difference.

The DCT processing order of the AC-coefficients using the zig-zag sequence illustrates that coefficients with lower frequencies (typically with higher values) are encoded first, followed by the higher frequencies (typically zero or almost zero) show in Figure 2. The result is an extended sequence of similar data bytes, permitting efficient entropy encoding.

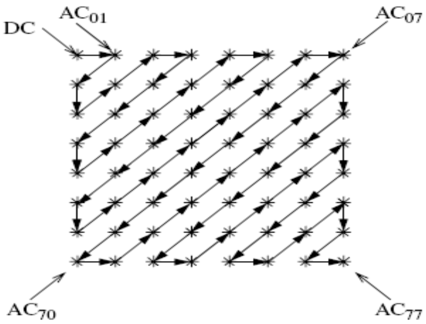


Figure 2: Zig-zag ordering of AC coefficients

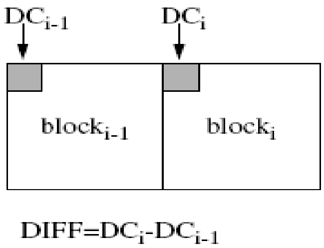


Figure 3: differential coding of DC

Step7: Finally, the last block in the JPEG encoder is the entropy coding, which provides additional compression by encoding the quantized DCT coefficients into more compact form show in figure 3. The JPEG standard specifies two entropy coding methods: Huffman coding and arithmetic coding [5]. The baseline sequential JPEG encoder employs Huffman coding. The Huffman coder converts the DCT coefficients after quantization into a compact binary sequence using two steps: (1) forming intermediate symbol sequence, and (2) converting intermediate symbol sequence into binary sequence using Huffman tables.

3.2 JPEG Decoder

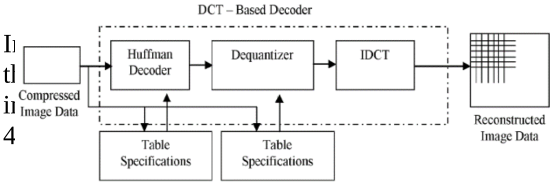


Figure 4: DCT-Based JPEG Decoder Processing Steps

Step1: First, an entropy decoder (such as Huffman) is applied to the compressed image data. The binary sequence is converted to symbol sequence using Huffman tables, and then the symbols are converted into DCT coefficients.

Step2: The dequantization is applied to the resultant coefficients using the following equation:

$$F_q(u,v) = F_q(u,v).Q(u,v) \qquad (2)$$

Step3**:** Then, the Inverse Discrete Cosine Transform (IDCT) is applied to the dequantized coefficients in order to convert the image from frequency domain into spatial domain.

4. IMAGE QUALITY MEASUREMENTS

Assessing image quality is crucial in different image processing applications. After creating and applying an image compression system, it becomes essential to assess its performance. This evaluation should enable a comparison of results with other image compression techniques. Image quality metrics offer a way to gauge the similarity between two digital images by leveraging variations in the statistical distribution of pixel values [9].

4.1 Peak Signal to Noise Ratio (PSNR)

It serves as a commonly employed measure of precision. A low Peak Signal to Noise Ratio (PSNR) indicates low image quality. The definition of PSNR is as follows:

$$PSNR = 10\log\left(\frac{L^2}{MSE}\right) \tag{3}$$

Where $L = 255$ is the dynamic range of the pixel values.
And

$$MSE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}[y(i,j) - x(i,j)]^2 \tag{4}$$

4.2 Weighted Peak Signal to Noise Ratio (WPSNR)

The Weighted Peak Signal to Noise Ratio (WPSNR) is an extension of the conventional PSNR, where each PSNR term is weighted by a local "activity" factor associated with the local variance [7].

$$WPSNR = 10\log\left(\frac{L^2}{\|(y-x).NVF\|^2}\right) \tag{5}$$

where

$$NVF = \frac{1}{(1+\theta\,\sigma_x^2(i,j))} \tag{6}$$

$$\sigma_x^2(i,j) = \frac{1}{(2L+1)^2}\sum_{m=-L}^{L}\sum_{n=-L}^{L}(x(i+m,j+n) - \bar{x}(i,j))^2 \tag{7}$$

$$\theta = \frac{D}{\sigma^2_{x\,max}} \tag{8}$$

where σ^2_{xmax} is the maximum local variance of a given image and $D \in [50,150]$ is a determined parameter.

4.3 Maximum Difference (MD)

A high Maximum Difference (MD) value indicates low image quality. MD is defined as follows:

$$MD = \max(\,|y(i,j) - x(i,j)|\,) \tag{9}$$

4.4 Correlation Coefficient

The correlation coefficient serves as a prevalent metric to quantify the similarity between two images. The correlation coefficient can take values between -1 and 1, with a stronger correlation approaching values closer to -1 or 1. The computation is carried out using the subsequent equation:

$$CF = \frac{\sum_{i,j}[y(i,j)-\bar{y}][x(i,j)-\bar{x}]}{\sqrt{\sum_{i,j}[y(i,j)-\bar{y}]^2\sum_{i,j}[x(i,j)-\bar{x}]^2}} \tag{10}$$

4.5 Structural Similarity Based Metrics

Another category of image quality measure is based on the assumption that the human visual system is highly adapted to extract structural information from the viewing field [8]. The error sensitivity approach estimates perceived errors to quantify image degradations, while this approach considers image degradations as perceived structural information variation. The structural Similarity *(SSIM)* index can be calculated as a function of three components: luminance, contrast and structure.

$$SSIM(x,y) = [l(x,y)]^{\alpha}\cdot[c(x,y)]^{\beta}\cdot[s(x,y)]^{\gamma} \tag{11}$$

This results in a specific form of the SSIM index:

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \tag{12}$$

where
$C_1 = (K_1 L)^2$, $K_1 << 1$ and $C_2 = (K_2 L)^2$, $K_2 << 1$.

5. EXPERIMENTAL RESULTS

Six test images (512×512, 8 bits/pixel) with different spatial and frequency characteristics, as shown in Figure 5: Lena, Baboon, peppers, Goldhill, Boat and Barb are used. Characteristics of test images are evaluated in spatial domain using spatial frequency measure (SFM) [6].

Figure 5. Image Database (size of 512×512

The spatial frequency measurement (SFM) indicates the overall activity level in an image. SFM is defined as follow:

$$SFM = \sqrt{(R)^2 + (C)^2} \quad (13)$$

$$R = \sqrt{\frac{1}{MN}\sum_{m=1 n=2}^{M,N}\left[x(m,n) - x(m,n-1)\right]^2} \quad (14)$$

$$C = \sqrt{\frac{1}{MN}\sum_{n=1,m=2}^{N,M}\left[x(m,n) - x(m-1,n)\right]^2} \quad (15)$$

Where R is row frequency, C is column frequency, x (m, n) denotes the samples of image, M and N are number of pixels in row and column directions, respectively. The large value of *SFM* means that image contain component in high frequency area [13].

a. Measuring Spatial Frequency (SFM)

The Spatial frequencies (SFM) and values computed for the above set of images are given in Table 1.

Test image Baboon has a lot of details and consequently large SFM. Large value of SFM means that image contains components in high frequency area. It returns that Baboon presents.

TABLE 1. spatial frequency measure of images

	Lena	Baboon	Peppers	Goldhill	Boat	Barb
SFM	14.042	36.5146	15.8446	16.1666	17.8565	29.4567

b. Evaluating Perceptual Quality

PSNR, wPSNR, MD, CF and SSIM values of each of the two approaches of JPEG compression are recorded in Table 2, 3,4,5, and 6 respectively. All values are recorded at *k*=8192

TABLE 2. PSNR values (in dB) of the images.

Method	Lena	Baboon	Peppers	Goldhill	Boat	Barb
Apr-1	32.2410	30.3528	31.5590	31.2419	31.8917	31.2373
Apr-2	34.5701	30.4406	34.1011	32.2553	33.6249	31.9630

In Table 2 we record the PSNR values of each of the two approaches of JPEG compression at k=8192. We note that the second approach provides better PSNR than the first one at the same *k*.

TABLE 3 wPSNR values (in dB) of the images

Method	Lena	Baboon	Peppers	Goldhill	Boat	Barb
Apr-1	133	147	185	113	153	142
Apr-2	92	147	130	88	109	108

TABLE 4 MD values of the images

Method	Lena	Baboon	Peppers	Goldhill	Boat	Barb
Apr-1	27.249	21.2859	26.4219	27.0946	25.8598	24.0606
Apr-2	31.0313	22.1589	30.5118	28.7770	28.5342	25.9047

The wPSNR values for each of the two JPEG approaches at k=8192 are listed in Table 3. We observe that at the same k, the second approach offers better wPSNR than the first.

In Table 4 we record the MD values of each of the two approaches of JPEG compression at k. we note that the second approach provides better MD than the first one at the same *k*.

TABLE 5 Correlation coefficient values of the images

Method	Lena	Baboon	Peppers	Goldhill	Boat	Barb
Apr-1	0.9728	0.8542	0.9773	0.9735	0.9687	0.9562
Apr-2	0.9887	0.8826	0.9912	0.9821	0.9832	0.9716

The CR values for each of the two JPEG approaches at k=8192 are listed in Table 5. We observe that at the same k, the second approach offers better wPSNR than the first.

TABLE 6 Structural Similarity values of the images

Method	Lena	Baboon	Peppers	Goldhill	Boat	Barb
Apr-1	0.7852	0.5265	0.7634	0.6922	0.7572	0.7171
Apr-2	0.8223	0.5279	0.7950	0.7128	0.7928	0.7309

Table 6 lists the SSIM values for the two JPEG approaches at k=8192. We find that the second approaches provide better SSIM than the first at the same k.

All above tables assure that the 2nd approach provides better image quality than the 1st one at the same *k*. Moreover, the 2nd approach is quite faster compared to that of 1st one. Figure 6 and figure 7 show the original and compressed images using different approaches at different values of *k*.

Figure 6. (a)Original image, (b),(c) compressed images using 1st and 2nd approach respectively at *k*=8192

Figure 7. (a)Original image, (b),(c) compressed images using 1st and 2nd approach respectively at *k*=163840

A comparison between the two approaches is presented by measuring the PSNR, wPSNR, MD, CF and SSIM for the compressed images using the two approaches at different values of *k*.

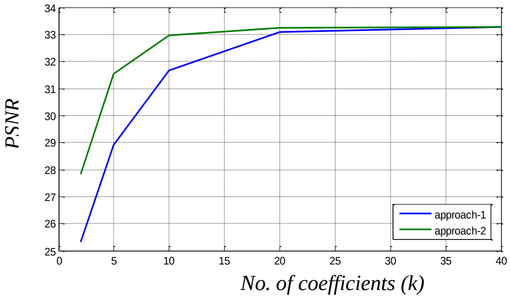


Figure 8: PSNR versus different values of k

Figure 8 represents the relation between the PSNR and number of selected coefficients for each of the two JPEG approaches. We note that the second approaches provide better PSNR than the first at the same k.

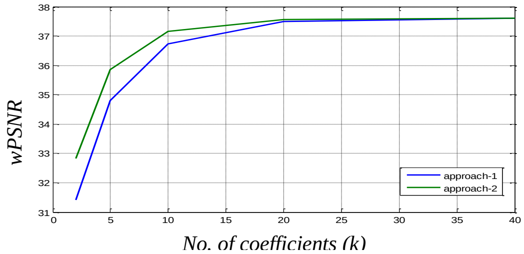


Figure 9: wPSNR versus different values of k

Figure 9 illustrates the relation between the wPSNR and number of selected coefficients for each of the two JPEG approaches. We note that the second approaches provide better wPSNR than the first at the same k.

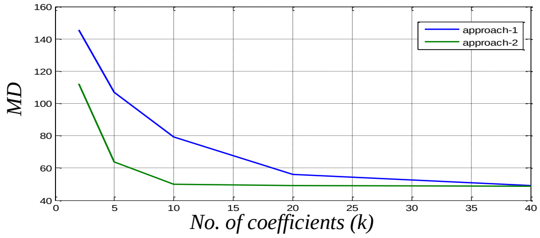
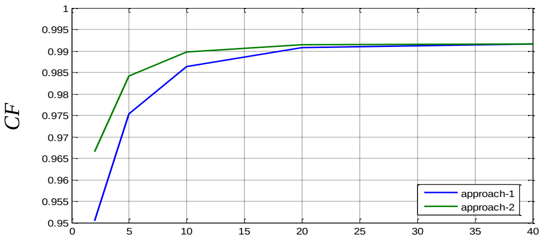


Figure10. MD versus different values of *k*

Figure 10 shows the relation between the MD and number of selected coefficients for each of the two JPEG approaches. We find that the second approaches provide better wPSNR than the first at the same k.



No. of coefficients (k)

Figure 11.CF different values of k

Figure 11 represents the relation between the CF and number of selected coefficients for each of the two JPEG approaches. We note that the second approaches provide better wPSNR than the first at the same k.

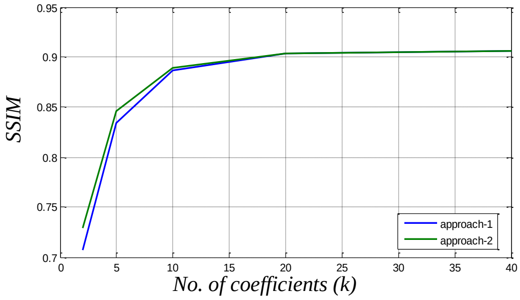


Figure 12. SSIM versus different values of k

Figure 12 illustrate the relation between the SSIM and number of selected coefficients for each of the two JPEG approaches. We remark that the second approach provides better wPSNR than the first at the same k.

From all the previous figures we assure that the second approaches provide better image quality than the first approaches in the same number of selected coefficients

5. CONCLUSION

This paper clarifies the advantage of choosing the coefficients to be quantized globally in achieving better perceptual quality. The experimental results emphasis the better quality of the compressed images resulted from the approach relying on quantizing the largest coefficients selected globally than the images resulted from the approach relying on quantizing the largest coefficients selected locally in each block. While JPEG is primarily known for lossy compression, future advancements might focus on improving lossless compression capabilities. This would be particularly beneficial for applications requiring perfect image reconstruction without any loss of information. As data security and privacy become increasingly important, future JPEG compression techniques may incorporate encryption and watermarking capabilities to protect sensitive information within images.

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