AN EXPERIMENTAL COMPARISON BETWEEN VARIOUS IMAGE COMPRESSION TECHNIQUES

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Abstract

Image is the most common type of digital data that is stored and transmitted in today's world. The development in technology brings advanced image capturing devices with higher quality. This results in acquiring a large storage space and bandwidth. To address these challenges image compression is evolved. Image compression helps in reducing the size of the image and maintaining quality. In this paper, we are going to discuss some of the image compression algorithms like Discrete Cosine Transform, Tetrolet Transform, and K-Means Clustering technique by compressing three sample images and compare their experimental results based on the quality metrics like Compression Ratio (CR), Peak Signal-to-Noise Ratio (PSNR), and Structural Similarity Index Measure (SSIM). This helps in understanding the performance of each algorithm based on various parameters.

Keywords *· Discrete Cosine Transform · Image Compression · K-Means Clustering · Tetrolet transformation ·Tetrominos ·*

1 Introduction

An image is defined as the binary representation of the visual information which can be stored electrically. In this modern era, there is substantial growth in digital information which challenges storage and transmission. We usually come across many applications of images in our daily routine like social media, satellite navigation, face recognition, and many more. These generate data on the scale of Petabytes per day. To address the challenges in storage and transmission of this, image compression must be performed.

Image compression is the technique performed to reduce the size of the image by eliminating redundant and unnecessary details. Image compression is broadly classified into two techniques, they are Lossless Compression and Lossy Compression. Lossless compression is achieved by eliminating unnecessary metadata without losing quality. Lossy compression is performed by eliminating the unidentifiable data from the image. This will end-up in partial data discarding with loss in the image quality.

In this paper image, compression techniques like Discrete Cosine Transform, Tetrolet Transform, and K Means Clustering-based image compression are discussed, and the experimental results are analyzed.

In remaining sections of this paper deal with the following components like section 2 deals with the explanation of the Discrete Cosine Transform and section 3 elaborates on the Tetrolet Transform and its algorithm. Session 4 deals with the K Means Clustering technique in image compression. In section 5 shows the experimental results obtained on multiple images using the above-explained algorithms and their analysis. Finally, the conclusion is presented in section 6.

2 Discrete Cosine Transform

The Discrete Cosine Transform (DCT) [4] can represent the signal in the frequency domain from the spatial domain format. For a particular image, the DCT can handle the information of the most significant parts in lesser number of coefficients which can help in the applications of the image compression. In DCT the frequencies and magnitudes are summations over the sinusoid of the image. The Discrete Cosine Transform is represented as:

$$F(u,v) = \frac{2C(u)C(v)}{\sqrt{MN}} X$$

$$\sum_{x=0}^{M-1} \sum_{y=0}^{N-1} co\,s\frac{(2x+1)u\pi}{2M} cos\frac{(2y+1)v\pi}{2N} f(x,y)$$

Where $C(\xi)$ is represented as,

$$C(\xi) = \begin{cases} \frac{1}{\sqrt{2}} & if\ \xi = 0, \\ 1 & otherwise. \end{cases}$$

Discrete Cosine Transform Algorithm:

Step 1: Input image: Load input image.

Step 2: Divide the Image into 8X8 blocks.

Step 3: Apply DCT for each block.

Step 4: Quantization of each block by dividing with Qmatrix.

Step 5: Rounding the quantized values and level shifting.

Step 6: Apply zigzag on the blocks and encode.

Step 7: Output Image: Compressed Image.

Here, f(x, y) represents the intensity of the pixel at row x and column y. F(u, v) represents the DCT coefficient. The DCT consists of the low frequencies at the upper left corner where the signal energy is high. Due to the compression, lower visible distortions are formed due to neglecting the higher frequencies which are accumulated at the lower right corner of DCT.

3 Tetrolet Transform

Tetrolet transform is a Harr type of Wavelet Transform which is used in image compression with low noise and maintains high quality.

Wavelet Transform can be expressed as follows:

$$F(p,q) = \int_{-\infty}^{\infty} f(t)\Psi^{*}_{(p,q)}(t)\,dt$$

Where * refers to the complex conjugate.

The main advantage of the wavelet transform is orthogonality, a high degree of smoothness, more energy compaction, and symmetry.

On the initial mother wavelet, the Harr wavelet is applied by imposing the following function to get the higher frequency information of the wavelet to the greater time resolution.

$$\psi(t) = \begin{cases} 1 & 0 \le t < 1/2, \\ -1 & 1/2 \le t \le 1, \\ 0 & otherwise. \end{cases}$$

Tetrominoes[2] are shapes that are applied on the image blocks to find the low pass and high pass coefficients for wavelet decomposition. Tetrominoes shapes are formed by joining four square boxes by their edges. There are five possible shapes are formed.

Tetrolet Decomposition Algorithm[1]:

Input: Load input image.

Step 1: Split the image to 4X4 blocks.

Step 2: identify the sparsest tetrolet in each block.

Step 3: Rearranging the low-pass and high-pass coefficients to construct 2X2 blocks.

Step 4: Tetrolets with high-pass coefficients are to be stored.

Step 5: repeat Step 1-4.

Output: Compressed Image.

The computational power of the wavelet transform is low, but on applying tetrolet transform the computational power increases with high compression ration and with preserving the image quality.

4 K Means Cluster

K Means Cluster Algorithm is a clustering algorithm[3] used to create clusters based on the similarities of the data points. In image compression, k means clustering is performed based on the image pixel values are clustered together by calculating the Euclidean distance between the pixels and assigned to the centroids. Iterating the process will reduce the pixel values and the image is getting compressed.

K Means Image Compression Algorithm:

Step 1: Load the Image and read as an array.

Step 2: Initialize the K value to obtain the initial clusters.

Step 3: Consider the cluster centers randomly based on K.

Step 4: Calculate the distance between each pixel and the cluster centers and assign to the nearest centroid.

Step 5: Calculate the mean of pixels in the cluster to update the cluster centroid.

Step 6: Repeat steps 4 and 5 until the convergence in centroids is obtained or the completion of iterations.

Step 7: Reconstruct the Image based on the obtained clustered data.

Initially, consider the K value for the number of centroids and randomly select $K(\mu_k)$ centroids from the input pixel data. Let the data be {a(1), a(2), a(3),...,a(M)}, where "a" represents the image pixels and "M" represents to the total number of image pixels. Calculate the distance $\sum \|a_i - \mu_k\|^2$ between each pixel value (a(i)), where i = 1,2,3,…,M and centroid μ_k. Then assign the pixel values to the nearest cluster of centroid with minimum distance. Centroid is to be updated by calculating the mean values of the pixels obtained in each of the cluster. This will act as the new centroids for every cluster. Repeat these steps until the change in the centroid is nil.

5 Experimental Analysis

Compression Ratio (CR): Compression ratio is defined as the ratio between the original image to the compressed image.

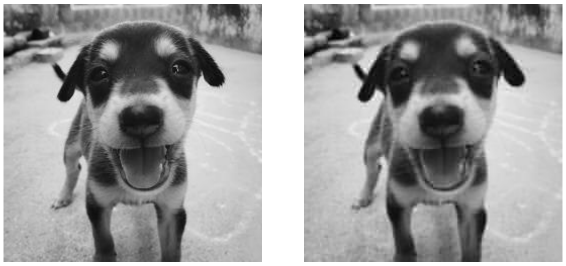
$$CR = \frac{Size\ of\ original\ image}{Size\ of\ compressed\ image}$$

Peak Signal-to-Noise Ratio (PSNR): The PSNR is the ratio of the maximum fluctuations in the image pixels to the cumulative squared error between the original image to the compressed image.

$$PSNR = 10\,log_{10}\left(\frac{R^2}{MSE}\right)$$

Structural Similarity Index Measure (SSIM): The SSIM refers to the identification of the perceptual structural difference between the original image to the compressed image. It explains the distortion in the visual structure between the images.

The metrics that are used for comparing the image quality of compressed image to the original image are
The experimental results of the DCT are shown below.

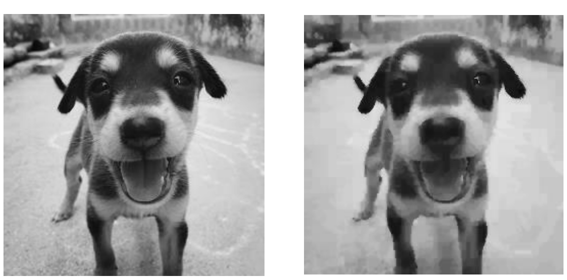


Original Image (1) DCT Compressed Image (1)
CR = 1.2030 PSNR = 32.0145 SSIM = 0.9112

Original Image (2) DCT Compressed Image (2)
CR = 1.1382 PSNR = 28.0520 SSIM = 0.8933

Original Image (3) DCT Compressed Image (3)
CR = 1.2213 PSNR = 23.1880 SSIM = 0.7754

The experimental results of the Tetrolet Transform (TT) are shown. The calculated quality metrics are tabulated in Tab. 1.

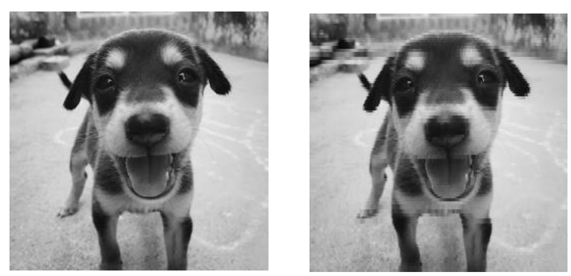


Original Image (1) TT Compressed Image (1)
CR = 1.5625 PSNR = 31.4514 SSIM = 0.8674

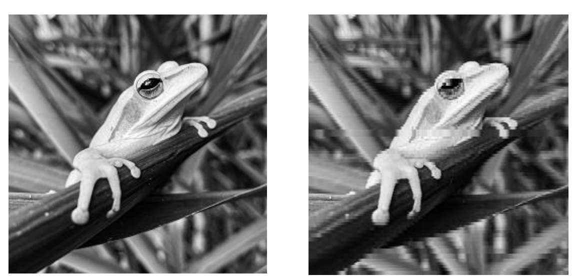
Original Image (2) TT Compressed Image (2)
CR = 1.3773 PSNR = 27.6909 SSIM = 0.8279

Original Image (3) TT Compressed Image (3)
CR = 1.4246 PSNR = 24.1539 SSIM = 0.7366

The experimental results of the K Means Clustering Algorithm (KMC) with number of clusters of K=128 are shown. In the table Tab. 1.
The experimental values obtained by taking K=64 is shown in Tab. 1. These values are useful in comparing the change in the quality of the image by reducing the number of clusters. These Images are not placed in this paper, but the quality metric values obtained are shown in table Tab. 1.



Original Image (1) KMC Compressed Image (1)
CR = 1.9160, PSNR = 31.3012, SSIM = 0.9304



Original Image (2) KMC Compressed Image (2)
CR = 1.9115 PSNR = 28.0626 SSIM = 0.9011

Original Image (3) KMC Compressed Image (3)
CR = 1.9203 PSNR = 24.9134 SSIM = 0.8561

The values of quality metrics obtained for the multiple algorithms are expressed in the table below.

Compression Technique \ Quality Metrics		CR	PSNR	SSIM
Discrete Cosine Transform	Image 1	**1.2030**	**32.0145**	**0.9112**
	Image 2	**1.1382**	**28.0520**	**0.8933**
	Image 3	**1.2213**	**23.1880**	**0.7754**
Tetrolet Transform	Image 1	**1.5625**	**31.4514**	**0.8674**
	Image 2	**1.3773**	**27.6909**	**0.8279**
	Image 3	**1.4246**	**24.1539**	**0.7366**
K-Means Algorithm (K=128)	Image 1	**1.9160**	**31.3012**	**0.9304**
	Image 2	**1.9115**	**28.0626**	**0.9011**
	Image 3	**1.9203**	**24.9134**	**0.8561**
K-Means Algorithm (K=64)	Image 1	**3.5990**	**27.9418**	**0.8496**
	Image 2	**3.6744**	**24.4722**	**0.7752**
	Image 3	**3.7226**	**21.7514**	**0.6896**

Tab. 1. Experimental values of CR, PSNR and SSIM for images using different algorithms **.**

The dimensions of the compressed images are the same as the original images but there is variation in the size of the image which can be identified using the Compression Ratio. The Images compressed using K-Means Clustering are having high Compression Ratios when compared to the other algorithms. This indicates the highest compression is achieved using the K-Means algorithm.

When comes to the Peak Signal to Noise Ratio for the Image(1) Discrete Cosign Transform is having high PSNR then comes to Tetrolet Transform and K-Means(K=128) algorithm which are having similar values.

We can see that K-Means performs better with the Image(3) type of images which maintains better quality with a high compression rate. SSIM values explain the structural similarity of the compressed image to the original image. Here K-Means Clustering is maintaining better SSIM values compared to other algorithms. With the decrease in the number of clusters let say K=64, The compression is highly achieved but the quality of the image is getting reduced.

Discrete Cosine Transform produces an image with better quality but the compression in size is very low. But Tetrolet Transform produces a similar Image quality with more compression in size. K-Means Clustering will provide better quality images with a large number of clusters and provides a better compression rate with a small number of clusters. When compare the compressed output images Tetrolet transform images are carrying more details than other types of compressed images.

6 Conclusion

This paper briefly discusses the image compression techniques like Discrete Cosign Transform, Tetrolet Transform, and K-Means Clustering algorithm. These techniques are applied on multiple images and the quality of the compressed images is expressed in CR, PSNR, and SSIM metrics. These metric values explain the Discrete Cosine Transform provides high-quality images but with a low compression rate. Tetrolet Transform provides similar image quality to DCT but with more compression rate and K-Means Clustering technique provide higher compression rate but this provides more quality for images having noise when compared to other images. It is evident that the K-Means technique provides compressed images more structurally similar to the original image when compared to other techniques. So this concludes that Tetrolet Transform can be useful in scenarios like medical images with better quality by preserving edges and countable compression.

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