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Medical Image Compression using DCT with Entropy Encoding and Huffman on MRI Brain Images

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ABSTRACT

Digital image compression is a modern technology which comprises of wide range of use in different fields as in machine learning, medicine, research and many others. Many techniques exist in image processing. This paper aims at the analysis of compression using Discrete Cosine Transform (DCT) by using special methods of coding to produce enhanced results. DCT is a technique or method used to transform pixels of an image into elementary frequency component. It converts each pixel value of an image into its corresponding frequency value. There has to be a formula that has to be used during compression and it should be reversible without losing quality of the image. These formulae are for lossy and lossless compression techniques which are used in this project. The research test Magnetic Resonance Images (MRI) using a set of brain images. During program execution, original image will be inserted and then some algorithms will be performed on the image to compress it and a decompressing algorithm will execute on the compressed file to produce an enhanced lossless image.

Keywords: *Image compression, Discrete cosine transform, Magnetic resonance images, Entropy.*

1. Introduction

An image is a visual portrayal of something that has been made or duplicated and put away in electronic structure and can be addressed as vector illustrations [1]. The digital image consists of pixels which are the smallest units of images that contain color intensities such as red, green and blue. During the transmission of an image or other media files, the files need to be compressed to gain bandwidth and power [2]. Image compression is done by deleting unnecessary or irrelevant information in the image and encoding the remaining information in a way that is not noticed in this transformation [3]. Image compression can be examined under two main topics. One of them is lossy compression which is also called as irreversible compression [4]. This is a data encoding method that approximates the original signal by removing some parts. Few available techniques of lossy compression are Quantization, Transform Coding, etc [5]. The second method is lossless compression that constructs the data without any loss so that there is no noise in the reconstructed signal and some techniques of lossless compression are Linear Predictive Coding, Multi-resolution Coding, etc [6]. The compression ratio is the fundamental distinction point between lossy and lossless compression paths. It is determined as the proportion between the quantity of pieces in the first document and the compacted record [7]. The rise of CR provides a gain in bandwidth and power in transmission but decreases image quality. Hence, some recurrence parts are erased without loss of value for wanted compression ratio in lossy compression procedures like Discrete Fourier Transform (DFT), Discrete Cosine Transform and Discrete Wavelet Transform (DWT). DCT is one of the lossy pressure strategies that address the sign as cosine capacities at various frequencies [8]. In contrast to DFT, DCT of sign comprises of genuine qualities, not perplexing qualities. By and by, DCT is liked over DFT in most change frameworks on the grounds that DFT coefficients require two times as much memory space as DCT coefficients [9],[10].

This work involves DCT to carry out picture compression for fluctuating square sizes and quality levels. It addresses a picture as an amount of sine floods of various sizes and frequencies. The DCT-2 capacity processes the

2-D discrete cosine change (DCT) of a picture. The DCT has a property wherein the majority of the outwardly huge data about the picture is gathered in only a couple of coefficients of the DCT. That is the reason DCT is in many cases utilized in picture pressure applications.

2. Literature Survey

2.1. Huffman Coding Simulation [11]

When Huffman coding is used to compress and encode image data, the probability statistics of the data gets carried out first and the probability of each symbol is obtained. Then this probability is sorted and coded to realize image data compression. The data after compression and decoding are consistent with the original data bits.

2.2. Run-length Coding Simulation [12]

Run-length encoding first binarizes then this binarized image is coded and decoded. The decompressed image is basically undistorted compared with the original binary image. The compression ratio of run-length encoding is very high and there is no loss compared to original image after encoding and decompression.

2.3. Predictive Coding Simulation [13]

Predictive coding achieves image compression by predictive error and the effect of image compression is judged by predictive error. The gray level of the image after predicted coding is greatly reduced and the image is obviously distorted.

2.4. Transform Coding Simulation [14],[15]

Transform coding divides image into 8*8 blocks and then 2D DCT transform is performed on each block. Then each image is inversely transformed by DCT. Images coded by DCT have obvious distortion compared with the original image but this does not affect the overall visual effect of the image.

3. System Implementation

3.1. Proposed Work

The bandwidth and storage are much cheaper and images typically contain a huge amount of useless redundancy. So, compressing images saves storage space and communication bandwidth with very little impact on image quality. The drawbacks are an increase in computing time (although this is cheap) and the cumulative degradation of images when lossy compression is used. Therefore, with these reasons the project is introducing Discrete Cosine Transformation using Entropy with Huffman coding to solve these problems. By using this technique, it finds very good applications for achieving high compression ratios with reasonably good PSNR values for most types of images.

3.2. System Architecture

This architecture diagram below in figure 1 explains the system as a whole of who will access it and how they will access. It simply explains on how the system process work from the user input (image to be compressed) to the output (decompressed image).

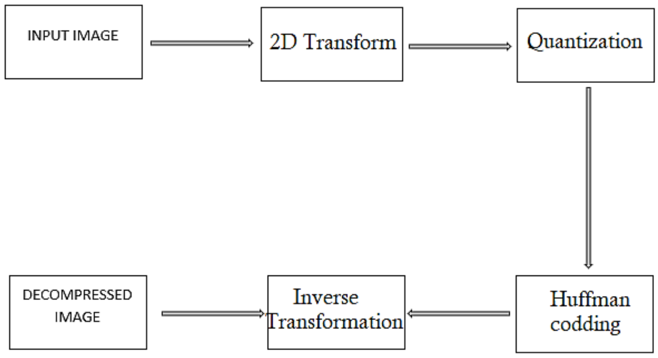

Fig.1. Architecture of the proposed system

3.3. System Development

3.3.1. System Flow Diagram

Data flow diagram is used to explain how the system will work based on the modules created. This gives an overall picture of how data will flow in the system from one point to another. Fig.2 briefly explains the system flow.

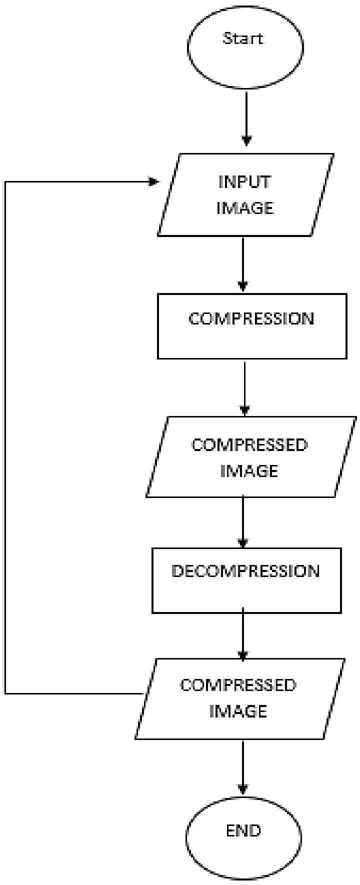

Fig.2. Data flow diagram of proposed work

3.4. Algorithms

3.4.1. Discreet Cosine Transformation

The emphasis of DCT has been an indexing and compression technique. There has been a great development in many post-processing methods for this approach. Despite the numerous benefits of DCT compression like fast decompression speed, high bit rate and resolution freedom, the most significant drawback is the high computing expense for this coding process.

DCT is a method of orthogonal transformation that decomposes an image to its spectrum of spatial frequency. To apply DCT, the image is divided into N-by-N pixel matrices. The N-by-N DCT basis matrix is constructed by using cosine basis functions for x and y dimensions. The formula below shows the implementation of DCT operation for each pixel on N-by-B sub matrices.

$$D(i,j) = \frac{1}{4}C(i)C(j)\sum_{X=0}^{7}\sum_{Y=0}^{7}P(Xx,y)\text{Cos}\left[\frac{(2x+1)i\pi}{16}\right]\text{Cos}\left[\frac{(2y+1)j\pi}{16}\right]$$

3.4.2. 2D - DCT

Image is processed as 8x8 blocks and one at a time. A 2-D DCT transform is applied to the block.

$$F(u,v) = \frac{C(u)C(v)}{4}\sum_{X=0}^{7}\sum_{Y=0}^{7}f(x,y)\text{Cos}\left[\frac{(2x+1)u\pi}{16}\right]\text{Cos}\left[\frac{(2y+1)v\pi}{16}\right]$$

$F(u,v)$= DCT Coefficient & $F(x,y)$ = Samples

3.4.3. Huffman Algorithm

This coding method is based on times of occurrence of image data. It uses lower number of bits to encode the data that occurs more frequently.

3.4.4. Huffman Encoding

This method checks statistical occurrence times. The pixels in the image are treated as symbols. The symbols that occur more frequently are assigned a smaller number of bits, while the symbols that occur less frequently are assigned a relatively larger number of bits. This means that (binary) code of any symbol is not the prefix of code.

3.4.5. Huffman Decoding

Before starting the compression of a data file, the compressor (encoder) has to determine the codes. It does that based on the symbol probabilities. The probabilities or frequencies have to be written on the output so that any Huffman decoder will be able to decompress the data. It normally adds just a few hundred bytes to the output. The algorithm for decoding is simple. Start at the root and read the first bit of the input. If it is zero, follow the bottom edge of the tree; if it is one, follow the top edge. Read the next bit and move another edge toward the leaves of the tree. When the decoder arrives at a leaf, it finds the original uncompressed symbol and that code is emitted by the decoder. The process starts again at the root with the next bit. Decoding a Huffman-compressed file by sliding down the code tree for each symbol is conceptually simple but slow. The compressed file has to be read bit by bit and the decoder has to advance a node in the code tree for each bit.

3.4.6. Quantization

Quantization reduces accuracy of the coefficients representation when converted to an integer. This project measures the threshold for visibility of a given basis function (coefficient amplitude that is just detectable by human eye). This work divides the coefficient by a value (appropriate rounding to integer). Quantization factor is 4, a half of the Q- is added to coefficient magnitude before it is divided and truncated.

4. Results and Discussion

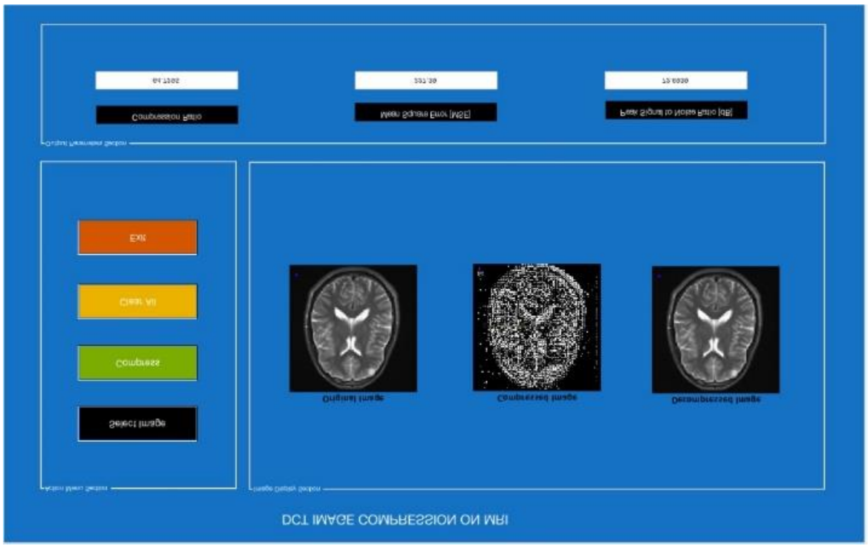

Fig.3. GUI of proposed system

4.1. Table of Comparison

Technique	Quality Level	Block Size	CR %	PSNR %	MSES
Huffman	H-man10	4x4	23.9	68.55	5715.56
	H-man50	4x4	22.8	67.17	762.45
	H-man90	4x4	19.86	69.22	431.65
	H-man10	8x8	33.54	59.34	4737.23
	H-man 50	8x8	24.5	68.44	815.67
	H-man 90	8x8	20.14	70.45	415.45
DCT	DCT 10	4x4	22.53	61.47	3012.39
	DCT 50	4x4	20.72	65.82	1106.74
	DCT 90	4x4	17.42	66.25	1000.73
	DCT 10	8x8	31.32	55.41	12161.7
	DCT 50	8x8	21.68	58.49	4754.37
	DCT 90	8x8	19.97	60.19	4042.04

MSE: Mean Square Error shows the squared errors between the original image and compressed image.

$$MSE = \frac{\sum_1^n [x - y]^2}{M \times N}$$

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$[x-y]^2$= Squared Error Image & $M \times N$= Rows × Columns

CR: Compression ratio shows the rate at which the original image has been reduced to.

$$CR = \frac{Uncompressed\ image\ file}{Compressed\ image\ file}$$

PSNR: Peak Signal to Noise Ratio shows the measure of peak errors.

$$PSNR = 10 \times \log_{10} \frac{R^2}{MSE}$$

5. Graphs for Analyzing the Research

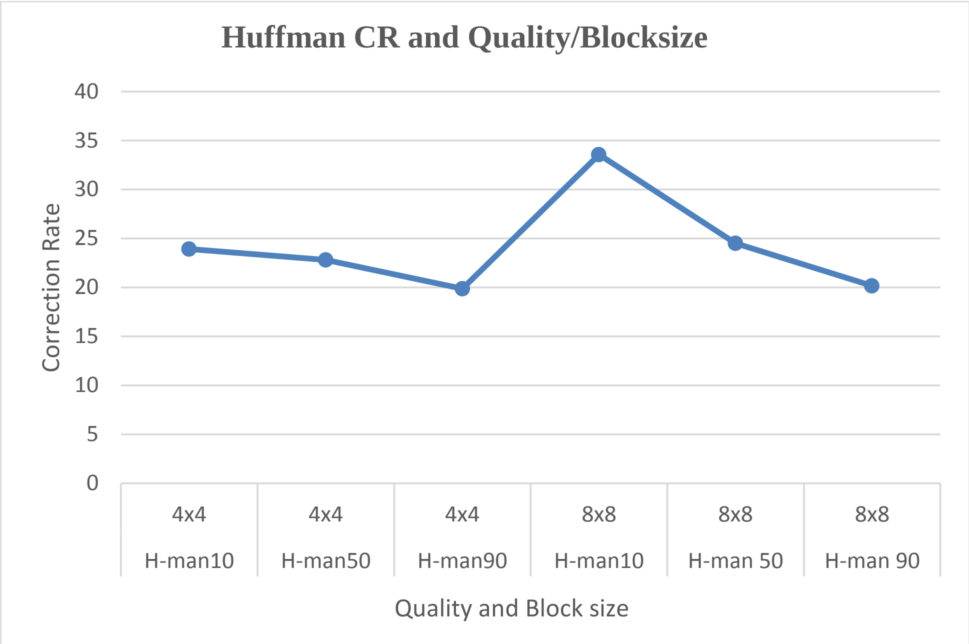

Fig.4. Huffman Analysis of Block size

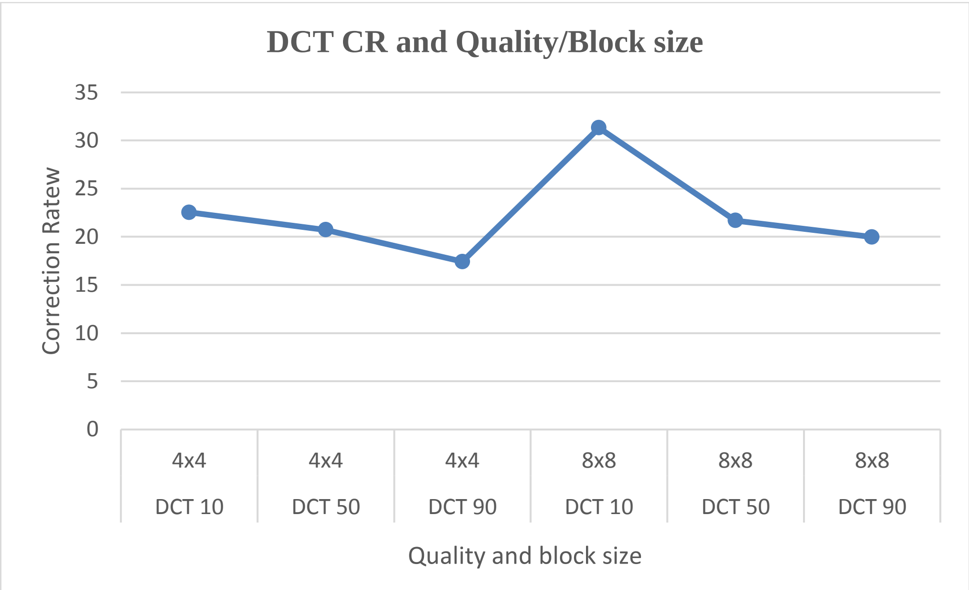

Fig.5. DCT Analysis of Block size

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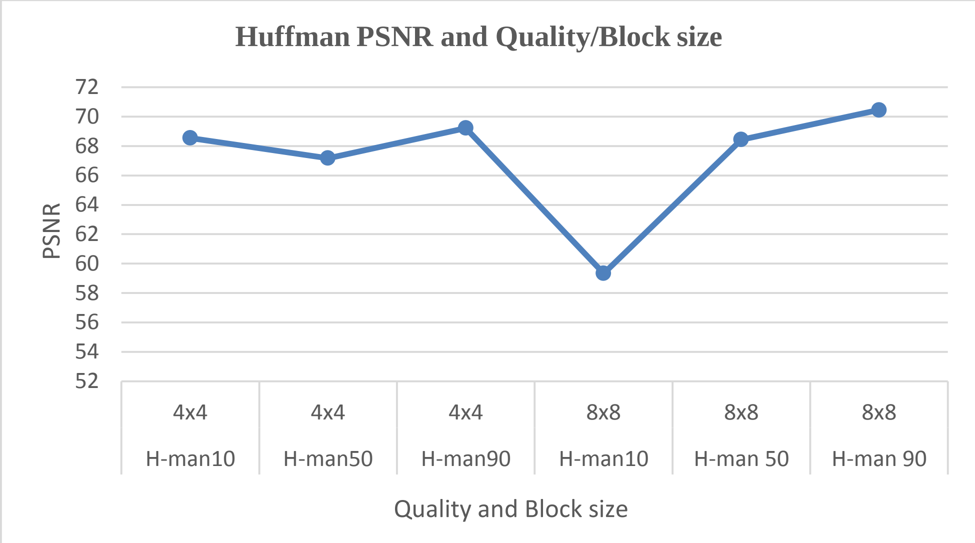

Fig.6. Huffman PSNR analysis

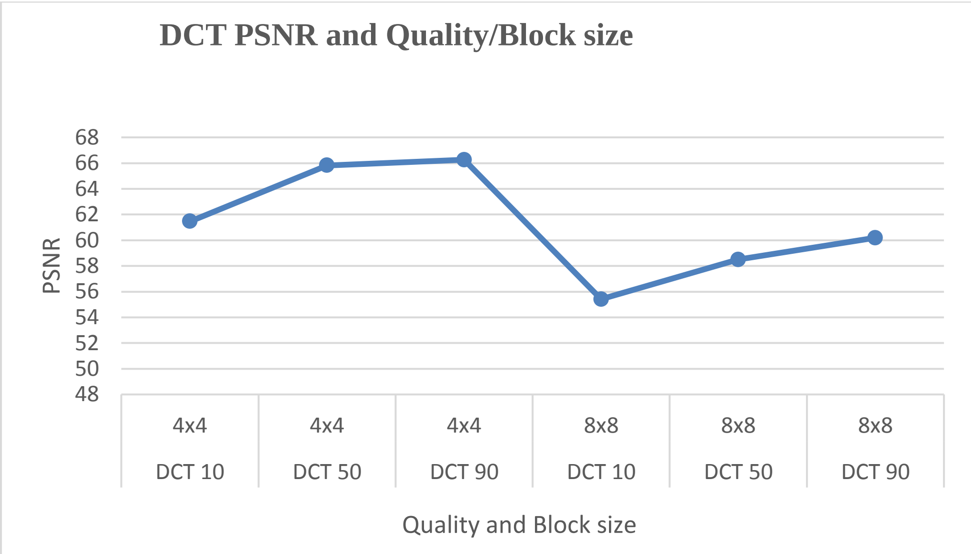

Fig.7. DCT PSNR analysis

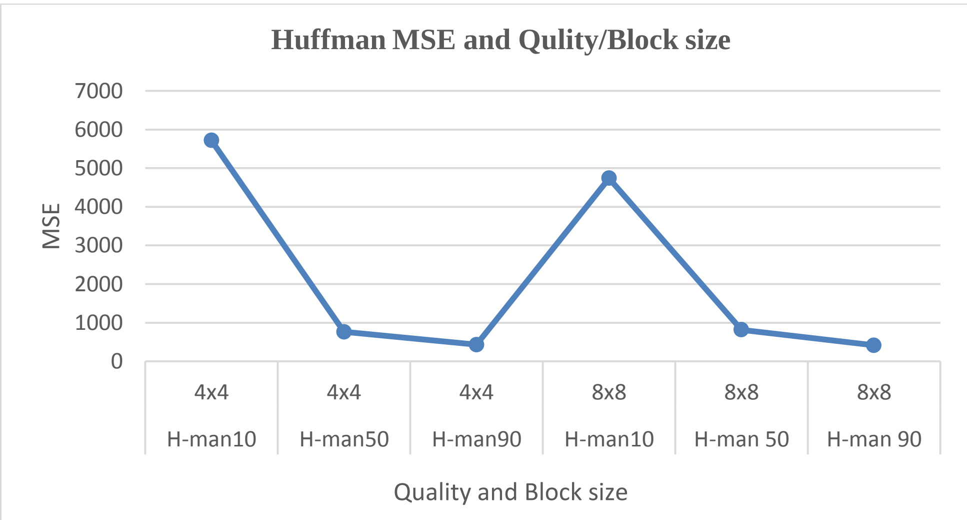

Fig.8. Huffman MSE analysis

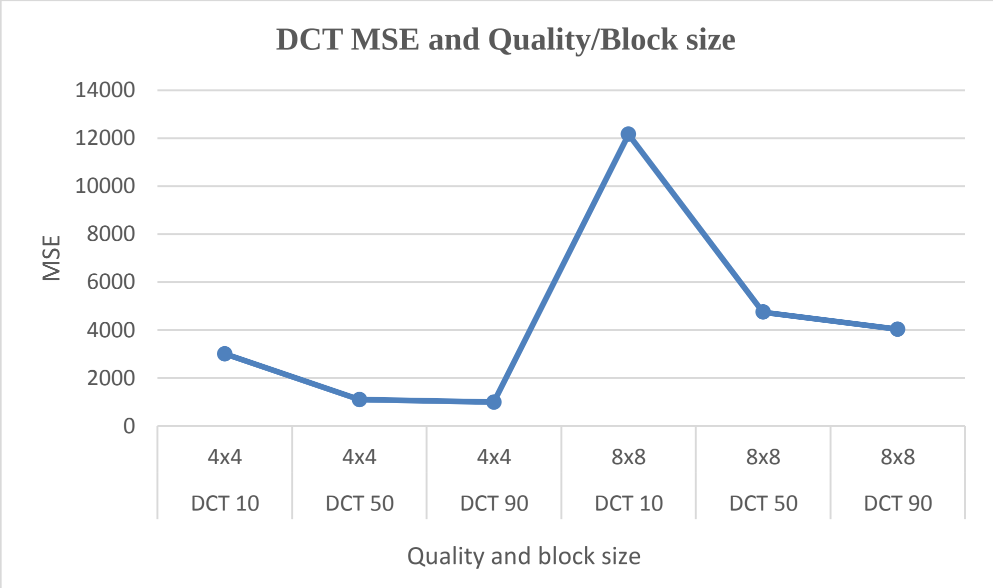

Fig.9. DCT MSE analysis

6. Conclusion

Image compression is widely helpful and important in our digital world. The DCT image compression algorithm shows an effective output of compressed image that has less quality loss. With use of Huffman algorithm, the results can be compared in the above outputs which were tested in MATLAB. The effectiveness of the algorithms are been measured using Compression Ratio, PSNR and MSE. Compression performance increases as the quality of increases too.

From the analysis carried out in the paper, the following conclusions can be drawn:

(a) The Entropy coding can be applied for improving the recovered image's quality and compression ratio significantly on different types of images.

(b) Perform scalar uniform quantization that affects the image quality, compression rate and encoding time.

(c) MRI images can be easily compressed by DCT compression and Entropy decomposition.

(d) Decreasing image size making less encoding time but this decreases image quality.

7. Future Enhancement

Further improvement in compression ratio and the PSNR values for the DCT coding can be achieved by considering the different dimensions of the range blocks, optimizing number of iterations. There are still some ways to improve the image quality, reduce the encoding time and increase the compression ratio to make fractal image compression by introducing an Entropy partitioning with overlapping ranges as a better solution.

This project can also apply other distributions to exploit self-similarity characteristics of images by using some advanced techniques (neural network, artificial intelligence, fuzzy logic) and the threshold value can be calculated automatically by different threshold methods (HSV and wavelet transform) and using different lossless algorithms to increase the image quality.

Declarations

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Competing Interests Statement

The authors declare no competing financial, professional and personal interests.

Consent for publication

Authors declare that they consented for the publication of this research work.

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