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Image Compression Technique Based on Fractal Image Compression Using Neural Network – A Review

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Author's contribution

The sole author designed, analyzed, interpreted and prepared the manuscript.

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ABSTRACT

Image compression research has increased dramatically as a result of the growing demands for image transmission in computer and mobile environments. It is needed especially for reduced storage and efficient image transmission and used to reduce the bits necessary to represent a picture digitally while preserving its original quality. Fractal encoding is an advanced technique of image compression. It is based on the image's forms as well as the generation of repetitive blocks via mathematical conversions. Because of resources needed to compress large data volumes, enormous programming time is needed, therefore Fractal Image Compression's main disadvantage is a very high encoding time where decoding times are extremely fast. An artificial intelligence technique similar to a neural network is used to reduce the search space and encoding time for images by employing a neural network algorithm known as the "back propagation" neural network algorithm. Initially, the image is divided into fixed-size and domains. For each range block its most matched domain is selected, its range index is produced and best matched domains index is the expert system's input, which reduces matching domain blocks in sets of results. This leads in the training of the neural network. This trained network is now used to compress other images which give encoding a lot less time. During the decoding phase, any random original image, converging after some changes to the Fractal image, reciprocates the transformation parameters. The quality of this FIC is indeed demonstrated by the simulation findings. This paper explores a unique neural network FIC that is capable of increasing neural network speed and image quality simultaneously.

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Keywords: Image compression; lossy compression; lossless compression; fractal image compression (FIC); neural network (NN); back propagation neural network (BPNN); range blocks; neural network (NN); peak signal to noise ratio (PSNR); mean square error (MSE); compression ratio (CR); bits per pixel (BPP).

1. INTRODUCTION

The need for computer animations, images, and video sequences applications has increased over the last several years for multimedia applications in telecommunications systems. Thus, compression of images and video is a critical topic. The goal of image compression is to reduce the amount of data required for a digital image. The other aim is to increase the transfer speed without reducing the quality of the image [1].

An image is a two-dimensional, processed visual signal. The images are usually shown in analog form. However, they are converted from analog to digital for processing, storage and transmission by computer applications. A Two-dimensional pixel array is essentially a digital image [2].

Compressing an image data produces vastly different results from compressing binary data. Images contain certain statistical properties which encoders specifically designed for them can exploit, which means that When using general-purpose compression programs, the outcome is less than optimal. [2].

Fractal Image Compression (FIC) is a relatively new image compression technique that is based on visual similarities in different sections. FIC is a block-based image compression algorithm that discovers and codes similarities between image regions, it has a number of advantages, including a quick decoding, and a high compression ratio. [3]. However, this method suffers from a long encoding time as its main drawback. This long encoding time arises from very large number of domain blocks that must be examined to match each range block. The number of range blocks with size of n × n, in an N × N image, is$(N/n)^2$, while the number of domain blocks is $(N-2n+1)^2$. Consequently it can easily be shown that the computation for matching range blocks and domain blocks has complexity of $O\,(N)^4$, several methods have been proposed to overcome this problem [4].

An artificial neural network (ANN), also known as a "neural network" (NN), is a mathematical or computational model that is based on biological neural networks. It is made up of an interconnected network of artificial neurons that process data using a connectionist approach to computation. Most ANNs are adaptive systems that change their structure based on external or internal information that flows through the network during the learning phase [5].

In data compression, two terms are commonly used: lossless compression and lossy compression. Lossless compression employs a set of algorithms that allows the original data to be precisely reconstructed from the compressed data. Lossy algorithms do not allow for accurate reconstruction of the original data, and there is some information loss during compression [6].

1.2 Principle of Image Compression

Image Compression provides a solution of reducing the number that the digital image needs to represent. Remove one or more of the three fundamental redundancies, we can achieve compression by either:

1. Spatial redundancy or correlation of nearby pixels.
2. The correlation of different color planes or spectral bands results in spectral redundancy.
3. Psych-visual redundancy is based on the characteristics of the human visual system.

When spatial or spectral patterns between pixels and color elements are common, spatial and spectral redundancies occur, while psychological or psychological redundancies are due to human eyes' lack of sensitivity to certain spatial frequencies. Different techniques can also be used to compress images to reduce storage sizes and space. [2].

2. COMPRESSION METHODS

Over the last two decades, different compression methods to address the major problems of digital imaging have been created. These modes of compression may be categorized as lossy or lossless. Lossy compression can reach a 50:1 or higher compression ratio because it permits a reasonable degradation. However, the original data cannot be entirely recovered. However, the lossless compression can fully retrieve the original data, which reduces the compression ratio to about 2:1.

For medical applications, lossless compression was required since the original image is not damaged because it allows a proper description [2,7].

2.1 Lossy Compression Methods

In general, the majority of lossy compressors showed in (Fig. 1) are three-stage algorithms each in step with the below three redundancies.

The original image could not be recovered from the compressed data exactly in this compression form. Because of certain data losses. Compared to lossless compression, this results in significantly higher compression ratios. The first step is a transformation to remove the redundancy between the pixels to efficiently package information. A psycho-visual redundancy quantizer is then used to represent packed information even less bits than possible. The quantized bits are then effectively encoded so that the coding redundancy is more compressed [2,8].

Lossy methods are particularly suitable for natural images like photographs where small loss of fidelity are suitable to reduce transform coding considerably.

- Discrete Cosine Transform (DCT).
- Discrete Wavelet Transform (DWT).
- Fractal Compression.

2.2 Lossless Compression Methods

This form of compression allows the original image to be extracted from compressed data. It is usually used for discrete data like text, computer information, web information and certain types of image and video information. Two-stage algorithms typically are lossless compressors (Fig. 2). The first step would transform the original image into a different format where the redundancy between the pixels is reduced. Second step is to remove the coding redundancy by using an entropy encoder. The lossless compressor is a perfect reverse compressor operation.

Medical images may usually be compressed to around 50 percent of their original size without loss. Bonceletet al.34 tested three entropy coding methods with an application in digitized radiographs for lossless compression and found that a bit rate of approximately 4 to 5 Bit Per Pixel (bpp) is best Tavakoli 35, 36 applied several lossless coding techniques to MR images and registered a compression up to about 5 to 6 pp with LZ (Lempel-Ziv) [2,8].

Methods for lossless image compression are:

- Run-length encoding – used as default method in PCX and as one of possible in BMP, TGA, TIFF.
- DPCM and Predictive Coding
- Entropy encoding
- Adaptive dictionary algorithms such as LZW – used in GIF and TIFF.
- Deflation – used in PNG, MNG, and TIFF.
- Chain codes.
- Huffman Encoding.

2.3 Fractal Image Compression

Fractal image compression is a Lossy Compression Technique type, creating iterated functional framework by Michael Barnsley in 1988, which provides a better-quality image than most other compressed image methods [9]. FIC is a fractal image compression that searches for and reads entire blocks to detect and decode relations between distinct regions. There are two main advantages of modifying fractal data images. Firstly, the initial data used to create the fractal has more memory than required the second advantage is that the image can be scaled or reduced by mathematical data, without altering the image's detail. [10,11,12].

A key feature of this algorithm is color partitioning the image using various normal image processing methods, like edge detection, spectrum analysis, and segmentation. Fractal systems apply different methods to each type of image part and create symmetrical and asymmetrical images. Fractal image compression is the usual example of an asymmetrical strategy. [13]. This algorithm uses image compression less than Huffman Coding to compress the 512×512 image files. The fractal algorithm can be used both to encode and to decode methods shown in (Fig. 3) [14]. Fractal encryption is used mostly for converting bitmap images into fractal codes. The conversion of traditional bitmap images to fractal data instantly demonstrates two significant advantages. Creativity is the first in skill, the ability to alter the image division's format. The second advantage is that the data is of particular size for each image and that data is used to store fractal codes less than the original data size in a specific input picture. This part of the process involves matching fractal with the fractal codes. This process isn't searching for exact matches, but instead is focused on 'best fit' for compression parameters. Fractal compression does not operate according to the traditional rules of data loss. [15,16,17].

2.4 Artificial Neural Networks

A variety of problems have been resolved through artificial neural networks, and they have shown to be superior to traditional approaches When working with noisy or inaccurate data, trust but verify. Decompression is another. Since neural networks are made to process complex patterns before generating simple ones, they work well for preprocessing input patterns. Neural networks are based on the organization of the human brain. The ability of neural networks to learn distinguishes them from other AI techniques. Through weight alteration of interconnections, the network "learns". A trained neural network's ability to provide a matching of previously unknown data is a key benefit of neural networks. Learning is normally achieved by preparation, where the training algorithm changes the relation weights iteratively (synapses). Back Propagation (BP) is a famous multilayer perceptron training algorithm. Learning algorithms have a massive effect on neural network efficiency, and the results differ depending on the application. As a result, the selection of appropriate learning algorithms is application based [18,19,20,21].

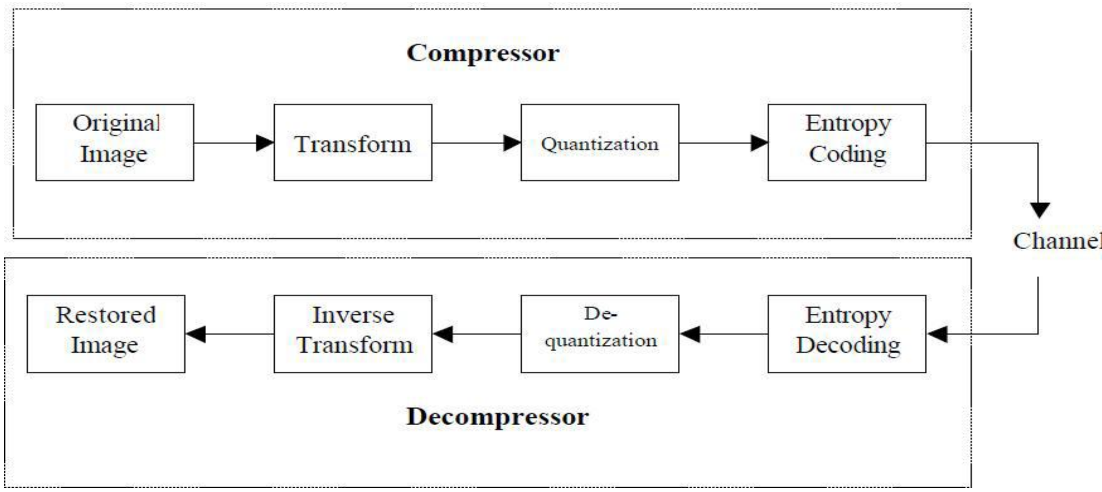

Fig. 1. Lossy image compression

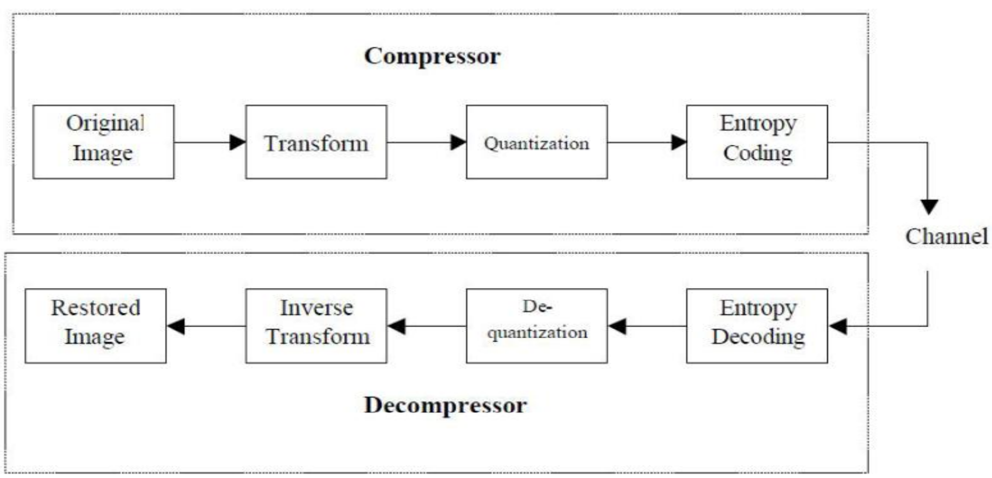

Fig. 2. Lossless image compression

The image compression problem is solved using a neural network architecture, as shown in (Fig. 4). In this architecture, input from a large number of input neurons is routed to a smaller number of neurons in the hidden layer, which is then fed to a large number of neurons in the network's output layer. A network of this type is known as a bottleneck feed forward neural network. The multilayer back propagation neural network is one of the most important types of feed forward networks.

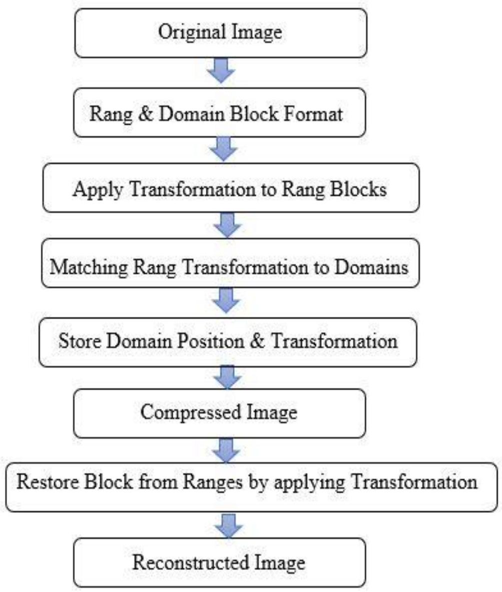

Fig. 3. Fractal image compression steps

The neural network architecture for image compression is having 64 input neurons, 16 hidden neurons and 64 output neurons and 1000 epochs according to the requirements. The input layer encodes the inputs of neurons and transmits the encoded information to the hidden layer neurons. The out- put layer receives the hidden layer information and decodes the information at the output. The outputs of hid- den layer are real valued and require large number of bits to transmit the data. The transmitter encodes and then transmits the output of the hidden layer 16 values as com- pared to the 64 values of the original image. The receiver receives and decodes the 16 hidden neurons output and generates the 64 outputs at the output layer [22].

2.5 Back-Propagation Algorithm

The increasing use of artificial intelligence techniques, such as neural networks in clustering, encoding and decoding, is one of the most exciting and very profitable trends of image compression. Since neural networks can generate simple patterns with fewer components before processing input models, they are well suited to this approach. The physical organization of the brain represents the organization of the external stimuli that are presented to it, which is a fascinating aspect of the brain. The back propagation algorithm was used to identify the domain cells in light of this. During the learning phase of Back Propagation the input layer-hidden layer-output layer weights are modified iteratively by the propagation algorithm. [23][21].

Back-propagation in Artificial Neural Networks is a common learning algorithm. The architecture of Feed-Forward (Fig. 4) Can estimate most high-precision and widespread problems. At the core of this algorithm is the error correction learning rule. Error propagation involves two passes through the network's multiple layers, one forward and one backward. [18].

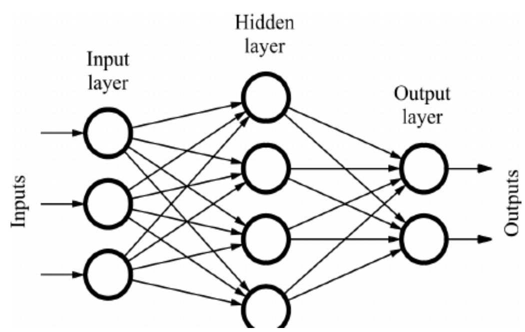

Fig. 4. Feed forward neural network architecture

2.6 Image Compression and Coding Method Based on Neural Network

In this case, a new technique for initializing the load between the input and unknown layers was used instead of randomizing the original weight. The Backpropagation algorithm is most versatile and is made up of a series of forward-feeding multi-level feed-forward neural networks. The input flows through the first layer, and the output is created. This process is repeated again and again, with several layers generating output that serves as an input for the next layer. After data are transferred to the input layer, information travels from the input layer to the output layer through the network, a process known as forward propagation. [10][24][25].

2.7 Deep Learning

Deep learning is a feature of an artificial intelligence (AI) system. This learning is an aspect of the human brain system. Alternatively, it mimics the neuron in the human brain. The network connection should be one neuron to the other neuron network, and the process should be repeated, so this is referred to as a deep neural network. Auto encoders, deep belief nets, convolution Neural Networks (CNN), Recurrent Neural Networks (RNN), and reinforcement learning to neural networks are some of the types. [26][27][28].

2.8 Performance Parameters

Many different image quality assessment parameters may be applied to a compressed images. Mean Square Error (MSE), Peak Signal to Noise Ratio (PSNR), Compression Ratio (CR), and Bits Per Pixel are the most widely used image quality parameters (BPP). The PSNR value is used to calculate the difference between a compressed and original image. Generally, the higher the PSNR value, the higher the quality of the compressed image. [15][29].

2.8.1 Mean square error (MSE)

One of the parameters used to assess the accuracy of a compressed image is the mean square error. If the MSE value is lower, the quality of the compressed image would improve. The MSE equation is as follows:

$$MSE = \frac{1}{MN}\sum_{X=1}^{M}\sum_{Y=1}^{N}\left[\int(x,y) - \int^{'}(x,y)\right]^2$$

Where $\int(x,y)$ is the original input image, $\int^{'}(x,y)$is compressed image and M, N are the dimensions of the images.

2.8.2 Peak signal to noise ratio (PSNR)

The ratio of input image size to Mean Square Error square is (MSE). The compressed image quality is also enhanced when PSNR is high.

$$PSNR = 10\ log_{10}\left[\frac{M*N}{MSE^2}\right]$$

Where, $M * N$ is the size of an input image.

2.8.3 Compression ratio

A useful compression ratio in image compression is the Compression Ratio which can be specified as the uncompressed image size divided by the compressed size.

$$Compression\ Ratio\ (CR) = \frac{UNCOMPRESSED\ IMAGE\ SIZE}{COMPRESSED\ IMAGE\ SIZE}$$

2.8.4 Bits per pixel (BPP)

The bits per pixel ratio (BPP) would indicate how many input images can be stored within one pixel of the bit depth. [15].

$$Bits\ Per\ Pixel\ (BPP) = \frac{SIZE\ OF\ COMPRESSED\ FILE}{TOTAL\ NO.OF\ PIXEL\ IN\ THE\ IMAGE}$$

2.9 Literature Survey

Jacquin suggested it for the first time with the Fractal Image Compression in 1989. and after Jacquin, other papers offer varying perspectives on the issue. In this review you can read about fractal image compression's architecture. Some of the papers will reduce the number of bytes used to produce high compression ratio with less encoding time G.V. Maha Lakshmi, Dr. S. Rama Mohana Rao [30] a new fractal image compression proposed for MRI images has reduced the search and encode time used by the expert system during the encoding process in order to speed up the encoding process without seriously affecting the quality of the image. For the training of the expert system, BPNN is used. This reduces the coding time by reducing the search space by the proposed method. The experimental results show that fractal compression (FIC) based on neural network (NNN) is much better in terms of time encoding without degrading the image quality compared with the usual FIC that uses comprehensive research. The performance is significantly improved.

Wang et al [31] the method proposed is a way of adding associated weights to both the spatial and descriptor domains of the confined functionality, and this is useful to retrieve images from a database that includes a large number of images. It is possible to increase individual features with very small computational overhead capacity. This method has higher performance with less calculation and recovery accuracy, shown by the test results of benchmark tests.

Khafaji et al [32] proposed a compression approach that worked on image characteristic changes locally After gaining access to this data, an image is recomputed using polynomial approximation into less compressed blocks. Finally, a compressed result is encoded using Huffman encoding is improved upon.

Mohammed S. Mahaboob Ismail.B Basha et al [33] said improved image fractal image compression (IFIC) method for color images made for the variable block size. The image here is divided into blocks considering the maximum and minimum range. Here, the fixed block size range of 4 x 4 iterations and other existing methods. This card achieves a compression ratio of 20 and a signal-to-to-noise ratio of 30 decibels (PSNR) above average.

M.K. Revathy Jayamohan et al [34] show that the fractal image compression complexity is due mainly to a great number of comparisons required to find an adequate block matching domain that matches block ranges within the image. This article discusses the multi-way computational efficiency of tree research has been investigated for domain information storage. Cabin fields shall be listed as one or more local features of each domain in a B++ tree ordered.

2.10 Working of Image Compression Based on Fractals and Back Propagation Neural Network

A new compression algorithm for MRI images, which consists of three stages Training, Decoding, and Decompression. Reducing the search space and speeding up encoding: The primary goal of this compression method is the four sections are described below.

2.10.1 Expert system

One of the most successful approximate solutions for classical artificial intelligence problems is an expert system. The expert system, as defined by **Feigenbaum**, is “an intelligent computer program that uses knowledge and inference methods to solve problems that require experience and skilled people.” As a result, an expert system is a computerized system that simulates the ability of decision-making experts. This means that the expert system attempts to behave in every way like an expert. Knowledge in an expert system can be defined as experience or knowledge that is available through books, magazines, and scientists [35].

2.10.2 Training phase

A large number of identical images are used as input images during training, and each image is further sub-divided into regions of interest. At the first, a domain block is examined in order to match the range of that block in an image, and then a fractal code is output. The expert system was given the range indices, then optimized using the domain blocks, which proved to be its best. When you figure out how long the preparation time takes, count it as part of the encoding time. In the indexing phase, the expert system receives an input from the range of the image and generates a database of candidate blocks from it. The search would then be limited to the domain blocks that were returned. As a result, the search space is decreased while the encoding time is increased. The block diagram of the training phase (Fig. 5) is shown below. [30].

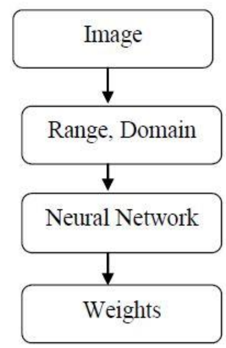

Fig. 5. Training Process

The FIC training algorithm for images in detailed steps is shown below:

1- Read input image and resize it to a standard size. Convert it to grayscale image.
2- Partition it into non overlapping blocks of any desired size, called Range blocks.
3- Partition the image into non overlapping blocks of any desired size, called Domain blocks. The size of range blocks can be less than or equal to the domain blocks.
4- Calculate all of the domain blocks' eight orientations.
5- Determine the block parameters for all range and domain blocks, such as mean, skewness, and standard deviation.
6- Initialize the targets based on some criteria.
7- Set the training and initialize the neural network parameters.
8- With the domain and range blocks as output, train the neural network.
9- As input, use domain and range blocks to simulate the network. The neural network must be saved.

10- Set the coefficients a, b, and j to zero.
11- Based on minimal distance metrics, compute the optimal values of a, b, and j for all range blocks in all domain blocks of the same class.
12- Save coefficients, a, b and j. Using Huffman coding.
13- Calculate the Compression Ratio for this algorithm and record the encoding time [3].

2.10.3 Encoding phase

The imaging domain range expert system accepts the index of the block used as input during the encoding process, and compiles a collection of parallel blocks to it. Then the search would only return domains which were in the returned list. This results in a smaller search space and increased encoding time. [10][36].

2.10.4 Decoding phase

As opposed to the most other ways of encoding, this technique involves an inverse transformation procedure in which the transformations parameters are applied to an initial image, and the fractal image emerges after a minimum of ten iterations. Initially, the MRI image is divided into a set of pre-defined size known as Blocks (Br), and the block operation takes place to average the four latest pixel intensity into each Block of data. First, a reduced image is extracted from the full image. Next, the best matched domain index, scaling parameter, and offset values are used to return a query. The reduced domain block's pixel values are computed based on the pixel rotation, after which they are mapped into the desired resolution and plotted in the desired orientation. Iteration is all or nothing. If ten iterations have been completed, the final image will be decompressed. [10][36].

2.11 Comparison of Different Approaches of FIC Techniques for Medical Image

In terms of PSNR, compression ratio, and encoding time, Table I show the comparison of the gray level Barbara fractal compression by means of comprehensive search, neural networks, and HGANN techniques with size 256 X 256. Table 1 shows that when HGANN is used instead of other conventional methods, the PSNR and compression ratio are increased [5].

Table 2 summarizes the output of various forms of FIC techniques for medical images used in this review in terms of encoding time. The following conclusions can be taken from the findings.

- The Quad-FIC works better than the fixed FIC, with a reduction in the quad-FIC encoding time from 109.16 sec to 6.7 sec.
- The FPGA Quad FIC has a superior encoding time performance.
- Quad FICs show better performance than quad FICs without neural networks with the neural network. [37]

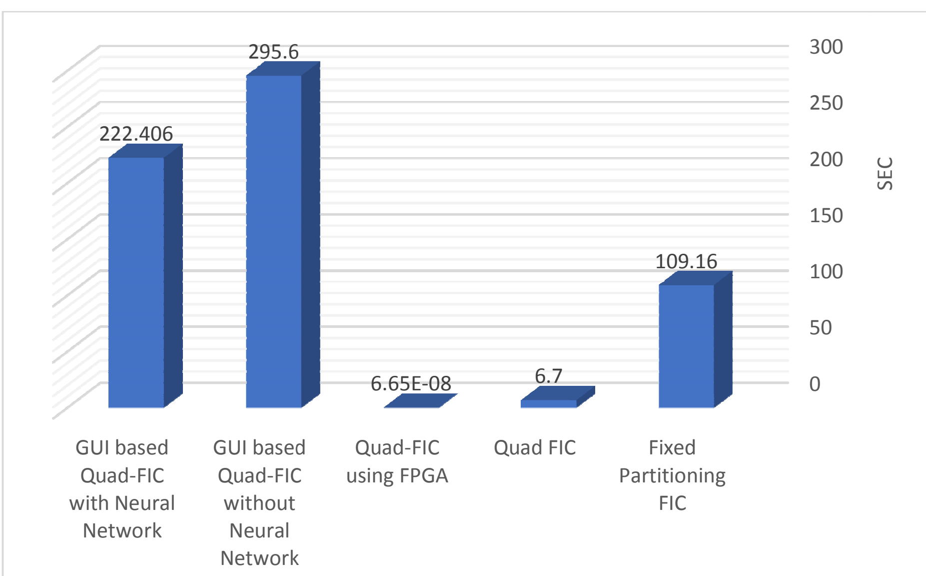

Fig. 6. Comparison of different Approaches of FIC techniques for Medical Images

Table 1. Comparison of FIC employing FIC and FIC with neural network techniques

Image	PSNR (db)			Compression ratio (dpp)			Encoding time (sec)		
	FIC	**FIC with NN**	**FIC with HGANN**	**FIC**	**FIC with NN**	**FIC with HGANN**	**FIC**	**FIC with NN**	**FIC with HGANN**
Barbara	32.674	29.788	30.05	1.2:1	6.73:1	6.73:1	8400	2800	2978
Butterfly (color image)	28.534	24.632	24.978	1.1:1	6.73:1	6.73:1	25000	7500	7590

Table 2. Performance of different FIC techniques on medical image of Size 256x256

Parametric indicator	Fixed partitioning FIC	Quad FIC	Quad-FIC using FPGA	GUI based Quad-FIC without neural network	GUI based Quad-FIC with neural network
Encoding Time	109.16 sec	6.7 sec	66.45 nano sec	295.6 sec	222.406 sec

3. CONCLUSION

A neural network based method of image compression is mentioned in this article. Most compression techniques are useful, and a new compression technique that offers a better compression ratio is being developed every day. Image compression is one of the most critical processes for digital image processing. Because of the limited storage space and bandwidth, vast amounts of digitized clinical data must be compressed before transmission and storage in medical imaging. However, the longer encoding process applies to fractal image compression. This review focused on fractal image compression for MRI images by employing a neural network algorithm known as "back propagation," used to reduce the search space and encoding time for images, allowing the quality to be maintained while speeding up the process.

COMPETING INTERESTS

Author has declared that no competing interests exist.

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