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A Novel Algorithm for Image Compression Based On Fractal and Neural Networks

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Abstract: ***Fractal image compression technique which excludes the similarities between different regions of the image takes long time for encoding. An artificial intelligence technique like neural network is used to reduce the search space and encoding time for the MRI images with an algorithm called as back propagation neural network algorithm. Initially, MRI image is divided into ranges and domains of fixed size and the best matched domain is selected for each range block and its range index and best matched domain index are produced which acts as input to the expert system which results reduced set of matched domain blocks. Now, the search is done only in resulted set of domain blocks with fractal codes as output and decoding process is executed. This paper shows the neural network based FIC which produces high improvement in encoding time without degrading the image quality when compared to normal FIC.***

Keywords: **Fractal Image Compression (FIC), Neural Network (NN), Back Propagation Neural Network (BPNN), Iterated Function System (IFS), Expert System.**

I. INTRODUCTION

Information transmission places major role in giving the data related to particular events like video conferences, medical data transfer etc., where much image data is to be transmitted for this type of events. Storage of massive data online requires large memory. Hence to overcome this problem all the images are compressed and decompressed using several compression and decompression techniques. The main aim of the image coding is to represent the image data in as few bits as possible and simultaneously should maintain the high quality of the image required for an application. Image compression has two great purposes: reduction of time for image transmission and reduction of storage area [1]. Image data redundancy is a key for image compression. Fractal image compression (FIC) a lossy compression method [2], which is based on iterated function system through which better reconstructed image with good quality is obtained than the other image compressed methods which was invented by Michael Barnsley in 1988. FIC technique is applied on images of different modalities like MRI, CT SCAN, X-rays, Ultrasound etc. The two major benefits of changing images to fractal data. The first one is that the fractal data occupies less size of memory than the amount of memory used to store the original bitmap information. The second benefit is that since the data is mathematical, the image can easily be scaled up or down a size (zooming) without changing the detail of the image [3]. An artificial intelligence technique like neural network is used to reduce the search space and encoding time for the MRI images. A algorithm called as back propagation neural network algorithm is used to increase the speed of the encoding time. At the initial stage MRI image is divided into ranges and domains of fixed size and twice the size of the range is the size of the domain. A search is done to select the best matched domain for each range block and then its range index and best matched domain index are produced. This range block index is given as a input to the expert system which results reduced set of more or less matched domain blocks. Now the search is done only in resulted set of domain blocks and it produces set of Fractal codes as output. Thus the searching and time taken for encoding is also reduced. To decode, the transformation parameters are recursively applied to the original image with mean value which produces the fractal image after fewer than ten iterations. This paper shows the neural network based FIC which produces high improvement in terms of encoding time without degrading the image quality compared to the normal FIC which excludes exhaustive search. The rest of the paper is organized as follows: A brief review of some of the works in the literature that uses FIC and NN to accelerate the encoding time is given in Section 2. The basic concepts of FIC are described in section 3. The proposed algorithm for image compression based on fractal and BPNN is presented in Section 4. Finally the experimental results are shown in section 5 and the conclusions are provided in section 6.

II. RELATED WORKS

Our work has been inspired by a number of previous works available in the literature which uses Fractal and back propagation network for MRI image compression. To obtain higher compression ratios in medical images by preserving quality, a fractal method which uses adaptive PIFS based on variants of affine transformations and lossless compression methods was developed by Murray H. Loew, et al in which Polynomials of various orders were used to represent adaptively the similarity of grayscale based on the original details of the image. Sumathi Poobal and G. Ravindran has shown that the lossy compression methods can be used for medical image compression without degradation of the image quality in which DCT and Fractal Compression using Partitioned Iterated Function Systems (PIFS) were applied. Based on the results in medical image compression, DCT can be used if good picture quality is preferred and FIC is used for compressing the images for storage and transmission is the priority, without degrading picture quality diagnostically [6]. Dietmar Saupe, et al., have proposed a fuzzy version of clustering aiming at improving the reconstructed image quality while maintaining the advantage of the complexity reduction. They said medical imagery seems to be a suitable class of images for fractal image compression because of the inherent fractal nature of

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organic matter. They have also discussed the important issues of image quality for medical applications [4]. Ming-Sheng Wu, et al., has proposed a FIC using schema genetic algorithm. Utilizing the self-similarity property of a natural image, the partitioned iterated function system (PIFS) will be found to encode an image through genetic algorithm (GA) method. In SGA, the genetic operators were adapted according to the schema theorem in the evolutionary process performed on the range blocks. Such a method can speed up the encoder and also preserve the image quality [7]. Sumathi Poobal, and G. Ravindran , has proposed a methodology for the arrival of an optimum value of tolerance factor for compressing medical images. In their work, Fractal Image Compression was achieved by PIFS using quad tree partitioning. PIFS was applied on different images like, Ultrasound, CT scan, Angiogram, X-ray, Mammograms. In each modality approximately twenty images were considered and the average values of compression ratio and PSNR values were arrived [5]. Thakur Nileshsingh V. and Dr. O. G. Kakde , have presented an approach for fractal color image compression on Pseudo Spiral Architecture which determines the pixel's tri chromatic coefficients within the homogeneous blocks formed by hierarchical partitioning method. Then, each block represented by its mean value of the pixel's tri chromatic coefficient ratios, and just a one-plane image was composed. A traditional square structure was represented in Pseudo Spiral Architecture for compression. On this Spiral Architecture image fractal gray level image coding algorithm was applied, with median as the basis to get encoded image. Due to the minimization of color planes from three to one and Spiral Architecture, the approach proposed by the authors was faster than other fractal coding methods [8]. Chun-Chieh Tsenga et al., have proposed an approach for Fractal image compression using visual-based. Particle swarm optimization (PSO) method in which the visual information of the edge property was utilized to speed up the encoder and preserves the image quality. A direction map was built according to the edge-type of image blocks which avoids full search and which directs the particles in the swarm to regions consisting of candidates of higher similarity [9]. Cangju Xing , et al., have proposed a hierarchical classification matching scheme for fractal image compression which reduces the encoding time dramatically by partitioning the domain pools hierarchically [10]. Y Chakrapani and K Soundera Rajan, have presented a back propagation based neural network for fractal image compression to improve the computational time and compression ratio.

III. BASIC CONCEPTS OF FRACTAL IMAGE ENCODING

A. Iterated Function Systems

This is based on collage theorem [8] which consists of a collection of contractive transformation $\{W_i : R^{2\to} R^2 \mid i = 1 \text{ to } n\}$ which maps the plane R^2 to itself. The collection of transformation defines a map. With the input set S, we can compute $w_i(s)$ for each i, considering the union of these sets; a new set $W(s)$ is obtained. (i) When the w_i are contractive in the plane, the W is contractive in a space of subsets of the plane. (ii) if a contractive map W is given, on a space of images, then there is a special image called the attractor.

$$W(.) = \bigcup_{i=1}^{n} w_i(.)$$

IV. NOVEL IMAGE COMPRESSION BASED ON FRACTALS AND BACK PROPAGATION NEURAL NETWORK.

A novel fractal image compression algorithm proposed for MRI images, utilizes the self-similarity property of a MRI image and it comprises of three phases namely Training, Encoding and Decoding .The main aim of this compression technique is to reduce the search space and speedup the encoding time. These three phases are detailed in the following sub-sections.

A. Training Phase

In the training phase, similar MRI images high in number are taken as input images and each image is partitioned into range blocks and domain blocks individually. At the initial stage, the range block of one MRI image is compared with the domain blocks of the same MRI image to select the best matched domain block for that particular range block in an image and the fractal codes are given as output.

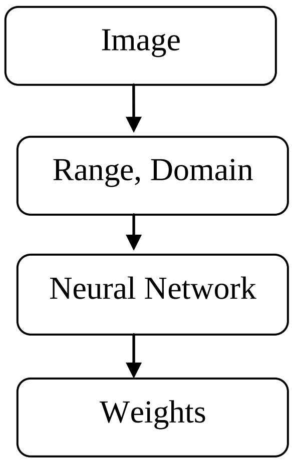

Fig 1: Training Process

Then the expert system has trained with the indices of range and its best matched domain blocks. The time taken in the training process will not be counted with the encoding time. During the encoding phase, the expert system takes the index of the range block of MRI image one by one as its input and it produces a set of domain blocks for the parallel range block. Then the search will be done only in the

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resulted set of domain blocks .Hence the search space is reduced and speed of the encoding time is increased. The figure 1 shown below represents the block diagram of training process.

1 Expert System Training Procedure:

The following are the steps involved in training process.

1. Divide the input MRI image of size (m x n) into a fixed block size, for instance, (Rx R). The obtained blocks are called range blocks and they are converted into a vector RB .

$$RB = [r_1, r_2, ..., r_k] \quad ;$$

$$where\ 0 < k \leq |RB|$$

2. In the block process operation the input image is reduced by averaging the intensities of four neighboring pixels and divided into fixed blocks of size (D x D) and put it into a vector. The resulting blocks are called Domain blocks DB.

$$DB = [d_1, d_2, ..., d_l] \quad ;$$

$$where\ 0 < l \leq |DB| \quad ;$$

$$where\ |DB| = 2 * |RB|$$

The following procedure repeated for k times to find a best matched domain block for each range block of an input image. Here k is the number of range blocks in the input image.

3. Now create a vector of size $|RB|$ and initialize the value of the vector with a^3.

$$DB^t_{best_{(k)}} \leftarrow a^3 \quad ;$$

$$where\ a = m/8 * n/8 \quad ;$$

$$where\ 0 < k \leq |RB|$$

4. Now consider a single range block and then convert it into a vector (V_{RB}) and compute the mean value ($\bar{V}_{RB}$) of the vector (V_{RB}).

$$V_{RB} \leftarrow RB_K \quad ;$$

$$where\ 0 < k \leq |V_{RB}|$$

$$\bar{V}_{RB} = \frac{\sum_{x=1}^{P} V^x_{RB}}{p} \quad ;$$

$$where\ p = |V_{RB}|$$

5. Extract a single reduced domain block and then convert it into a vector (V_{DB}). Now, calculate the mean value ($\bar{V}_{DB}$) of the vector (V_{DB}).

$$V_{DB} \leftarrow DB_l \quad ;$$

$$where\ 0 < l \leq |V_{DB}|$$

$$\bar{V}_{DB} = \frac{\sum_{y=1}^{q} V^y_{RB}}{q} \quad ;$$

$$where\ q = |V_{DB}|$$

6. Calculate the scaling parameter s and offset value o using the following formula.

$$s \leftarrow \frac{\left(V^x_{RB} - \bar{V}_{RB}\right)^T * \left(V^y_{DB} - \bar{V}_{DB}\right)}{\left(V^y_{DB} - \bar{V}_{DB}\right)^T * \left(V^y_{DB} - \bar{V}_{DB}\right)}$$

$$;\ where\ 0 < x \leq |V_{RB}|$$

$$;\ where\ 0 < y \leq |V_{DB}|$$

$$o \leftarrow \left(\bar{V}_{RB} - s\right)$$

7. Now for the current range block first initialize $Best_c$ as the best matched domain block and the value of $Best_c$ is calculated by using the following formula.

$$Best_c \leftarrow \left(V^x_{RB} - s * V^y_{DB} - o\right)^T * \left(V^x_{RB} - s * V^y_{DB} - o\right)$$

8. The $Best_c$ value is Compared against the element of the vector $DB^t_{best_{(k)}}$. If the obtained $Best_c$ is less than the current element of $DB^t_{best_{(k)}}$ vector and scaling parameter s is less than one then the current index l of the domain block , scaling parameter s and the offset value o are placed in the vectors $DB_{best_{(k)}}$, $DB^s_{best_{(k)}}$, and $DB^o_{best_{(k)}}$ using the below procedure, otherwise the process followed in the above steps is repeated with next domain block.

$$DB_{best_{(k)}} << l$$

$$DB^s_{best_{(k)}} << s$$

$$DB^o_{best_{(k)}} << o$$

$$DB^t_{best_{(k)}} \leftarrow Best_c$$

Then the steps from 3 to 7 are repeated to find the best matched domain block for the next range block. At the end,

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the indices of range block and its best matched domain block are obtained and are given as input to the Neural Network for training phase.

2 Back Propagation Neural Network

Back Propagation Algorithm is based on multi-layered feed-forward net and is the most versatile algorithm [12] in which the neuron in the first layer receives the input and it produces the output. This output will become the input (one of them) to the neurons in the next layer and this layer produces its output which will act as a input for the upcoming layer. This process continues until the last layer is reached. After all the layers process the input pattern presented to the network, the network is adjusted by using the errors. This process is called "back propagation" and it is done by adjusting the weights [15]. The back propagation of error algorithm[11 predicts the correct outputs from those obtained from experiments and generated ones. The back propagation network algorithm works as follows [13]. 1. After giving the input data to the input layer, information passes through the network from the input layer to the output layer generally called as forward propagation. During this period input and output states for each neuron will be set [16].

$$X_j^{[S]} = f(I_j^{[S]}) = f(\sum_i W_{ij}^{[S]*} X_i^{[S-1]}))$$

Where $X_j^{[S]}$: the current input state of the j[th] neuron in the current $[S]$ layer [14].

$I_j^{[S]}$: Denotes the weighted sum of inputs to the j[th] neuron in the current layer $[S]$.

f :Is conventionally the sigmoid function.

$W_{ij}^{[S]}$: denotes the connection weight between the i[th] neuron in the current layer $[S]$ and j[th] neuron in the previous layer $[S-1]$.

2. Based on the summed difference global error is generated and the output values of each neuron in the output layer is calculated [26].

The Normalized System error $E(glob)$ is represented by the equation

$$E(glob) = 0.5 * (r_k - o_k)^2$$

Where $(r_k - o_k)$ denotes the difference of required and calculated output values.

3. The obtained Global error is propagated back through the network to calculate delta weights and local error values for each neuron[26]. In this manner the regular decrease of global error is obtained [25].

$$E_j^{[S]} = X_j^{[S]} * (1.0 - x_j^{[S]}) * \sum (e_k^{[S+1]} * W_{kj}^{[S+1]}$$

Where $E_j^{[S]}$: scaled local error of the jth neuron in the current layer $[S]$

$$\Delta w_{ji}^{[S]} = lcoef * e_j^{[S]} * X_i^{[S-1]}$$

Where $\Delta w_{ji}^{[S]}$:Denotes the data weight of the connection between the current neuron and the joining neuron [26]. Here, $lcoef$ denotes the learning coefficient/ learning constant of the training parameters.

4. The obtained Synaptic weights are updated by adding delta weights to the current weights.

B. Encoding Phase Procedure

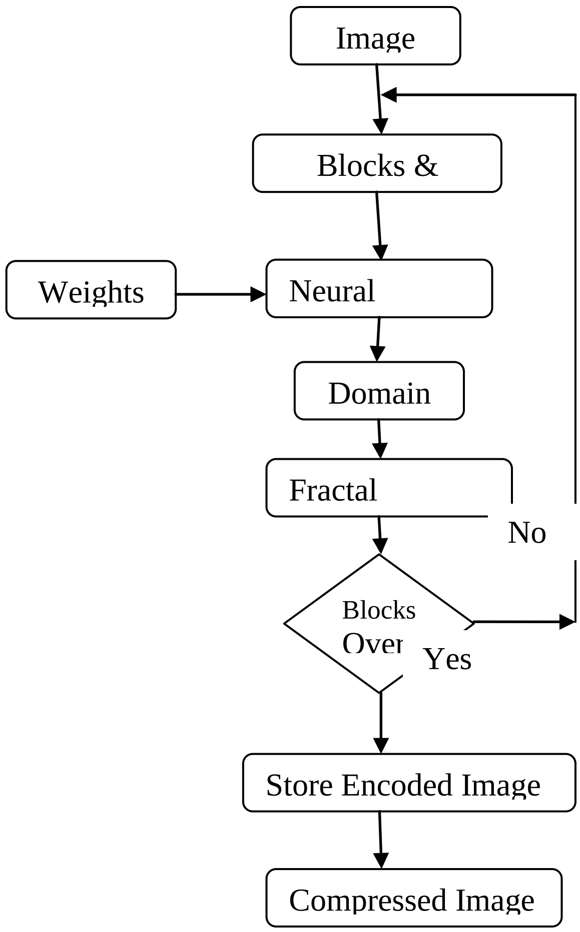

Fig 2: Fractal Image Encoding Process

The steps involved in encoding phase are listed as follows.

1. Divide the input MRI image (m x n) into blocks of fixed size, (Rx R). The resulting blocks are called range blocks which are then converted into a vector RB .

$$RB = [r_1, r_2, ..., r_k] \quad ;$$

$$where\ 0 < \text{k} \leq |\text{ RB}|$$

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2. Every (k) is given to the trained expert system which results reduced set of domain blocks indices as output vector.

$$DB = [d_1, d_2, ..., d_l] \quad ; \; where \; 0 < l \leq |DB|$$

3. The steps 3 to 7 described in the training section are repeated to find the best matched domain block from the reduced set of domain blocks. Then , the index of best matched domain block, the scaling parameter and the offset values are appended in the vectors.

4. Repeat steps 2 and 3 to find the best matched domain block for all the range blocks in the image.

After executing all the above steps, encoding phase results three vectors as output which are index of the best matched domain block $DB_{best_{(k)}}$ for each range block, the scaling parameter value of each domain block $DB^s_{best_{(k)}}$,and the offset value of each domain block. It produces fractal codes or compressed codes of image and these codes are used during decoding process to reconstruct the image.

C. Decoding Phase

Decoding is the reverse process of encoding is done in which the transformation parameters are applied recursively to an initial image with mean value and it will then converge to the fractal image after fewer than ten iterations. Initially, the input MRI image is partitioned into fixed blocks of size (R x R) are called range blocks RB and the block process operation is executed to reduce the newly formed image by averaging the intensities of four neighboring pixels and the resulted three vectors of encoding phase are considered now. A single block is extracted from the reduced image first. Then its corresponding best matched domain block index, scaling parameter and its offset values are retrieved from the vectors. The pixel values of the reduced domain block are then placed in the location in the range obtained by the orientation information after scaling and offsetting. All the range blocks constitute a single iteration. The decompressed image will be constructed after one to ten iterations. The decoding results are shown in figure 3

1 Decoding Procedure

The steps in the decoding procedure are described as follows.

1. Initially, form a new image of size (m x n) and place the mean value of the image in it then divide the newly formed image into a fixed block of size, (Rx R). The resulting blocks are called range blocks and converted into a vector RB .

$$RB = [r_1, r_2, ..., r_k] \quad ;$$

$$where \; 0 < k \leq |RB|$$

2. Now perform the block process operation in which the input image is reduced by averaging the intensities of four neighboring pixels to form one new pixel.

$$[\hat{I}] \leftarrow BP(I)$$

3. Generally , $DB_{best_{(k)}}$ vector contains indices of best matched domain blocks for all the range blocks of the image. Each Range block RB_k is listed based upon picking up an index value from the best matched domain block vector $DB_{best_{(k)}}$.

$$i \leftarrow DB_{Best_{(k)}}$$

4. Extract a single domain block from the block processed image $[\hat{I}]$. This extraction depends on the following procedure.

$$p \leftarrow ((i-1)\%|DB|)+1$$

$$q \leftarrow ((p-1)/|DB|)+1$$

$$col \leftarrow ((p-1)\%(n/8))+1$$

$$row \leftarrow ((p-1)/(n/8))+1$$

$$[DB_{(p)}] \leftarrow \hat{I}_{((row-1)*R+1:row*R,(col-1)*R+1:col*R)}$$

5. For each domain block eight transformation matrices (rotate/flip) are found during the encoding process and they are placed in a vector. Based on the calculated q value any one of the eight transformation matrix is selected and applied on the selected domain block which results a transformed matrix $DB_{(i)}$.

$$DB_{(i)} \leftarrow [DB_{(p)}]^T$$

6. The geometric transformed values, scaling parameter (s) and offset value (o) are Retrieved first. Then each element of transformed matrix $DB_{(i)}$ is multiplied by the scaling value $DB^s_{best_{(p)}}$ and added with the offset value $DB^o_{Best_{(p)}}$. Finally, the resulting matrix pixel values are placed in the position of range block RB_k .

$$RB_k \leftarrow DB^s_{Best_{(p)}} * DB_{(i)} + DB^o_{Best_{(p)}}$$

7. Repeat the steps 3 to 6 until all the range blocks are replaced.

8. The above listed process is repeated for all the range blocks which will constitute a single iteration. After one to ten iterations, the decompressed image will be constructed.

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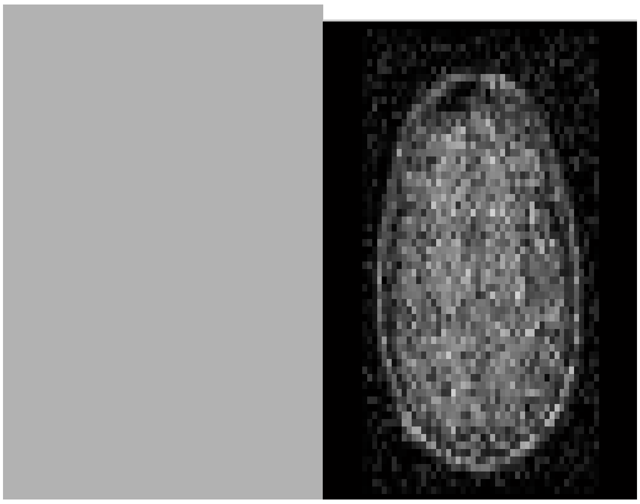
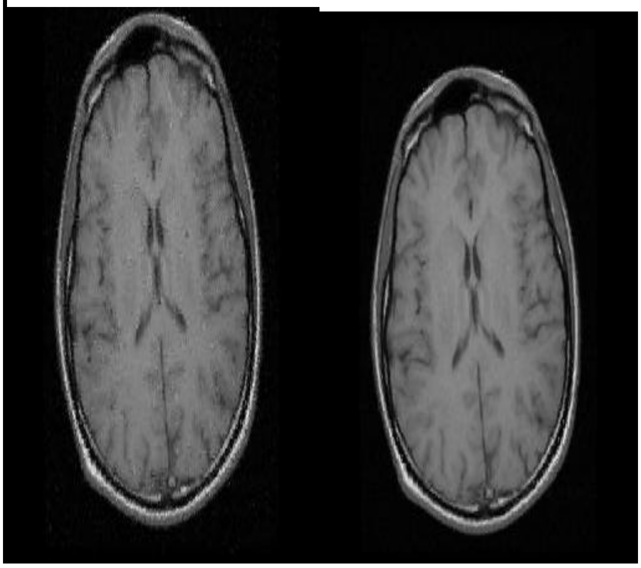
V. EXPERIMENTAL RESULTS

The proposed algorithm has been applied and tested with some brain MRI grayscale images. Five brain MRI images of dimension 256 x 256 presented in Table I are chosen to demonstrate our results. The input brain MRI image is divided into 4x4 blocks called ranges and 8x8 blocks called domain blocks, each of which is encoded separately and trained in the expert system using BPNN. Table I shows the PSNR, encoding time and compression ratio of the images for proposed methodology. Figure 3 shows the initial image and decoded image after 1, 3 and 5 iterations respectively. Figure 4 represents the decompressed images. The entire program is written in MATLAB 7.10 and all the tests were executed on a Pentium D'core 3MHz with 2GB of RAM size.



a) Initial Image with mean Value **b) Image after the first Iteration**



c) Image after the third Iteration **d) Image after the fifth Iteration**

Fig 3: Decoded image after 0, 1, 3 and 5 iterations

TABLE 1: PERFORMANCE MEASURE

Image	Time (Sec)	PSNR (dB)	Compression Ratio
1	34.02206	39.15	3.6226
2	33.75805	34	3.7500
3	33.77993	36.78	3.6994
4	33.99914	34.83	3.7500
5	33.8518	35.49	3.7573

Here, the proposed methodology is compared with the General FIC method, in terms of PSNR and encoding time and the obtained results of encoding process are summarized in the Table II.. The time taken for encoding is computed to show the fastness of the proposed compression scheme. Table II shows the encoding time comparison between the usual FIC and the proposed approach. The decoding process is carried out in an initial image with all pixels having the mean value of the image. Thus the experiment results show that our neural network based FIC algorithm can reduce the encoding time and produces the high quality decompressed image.

Table II: ENCODING TIME COMPARISON

Encoding Time (in Seconds)	
General FIC	**Proposed method**
43.78	33.88

Table III represents the PSNR comparison between proposed methodology and normal FIC method.

TABLE III: PSNR COMPARISON

Encoding Time (in Seconds)	
General FIC	**Proposed method**
27.21	36.05

Based on the obtained results, we observed that our proposed methodology compressed the images with better PSNR and Compression Ratio and achieved less encoding time.

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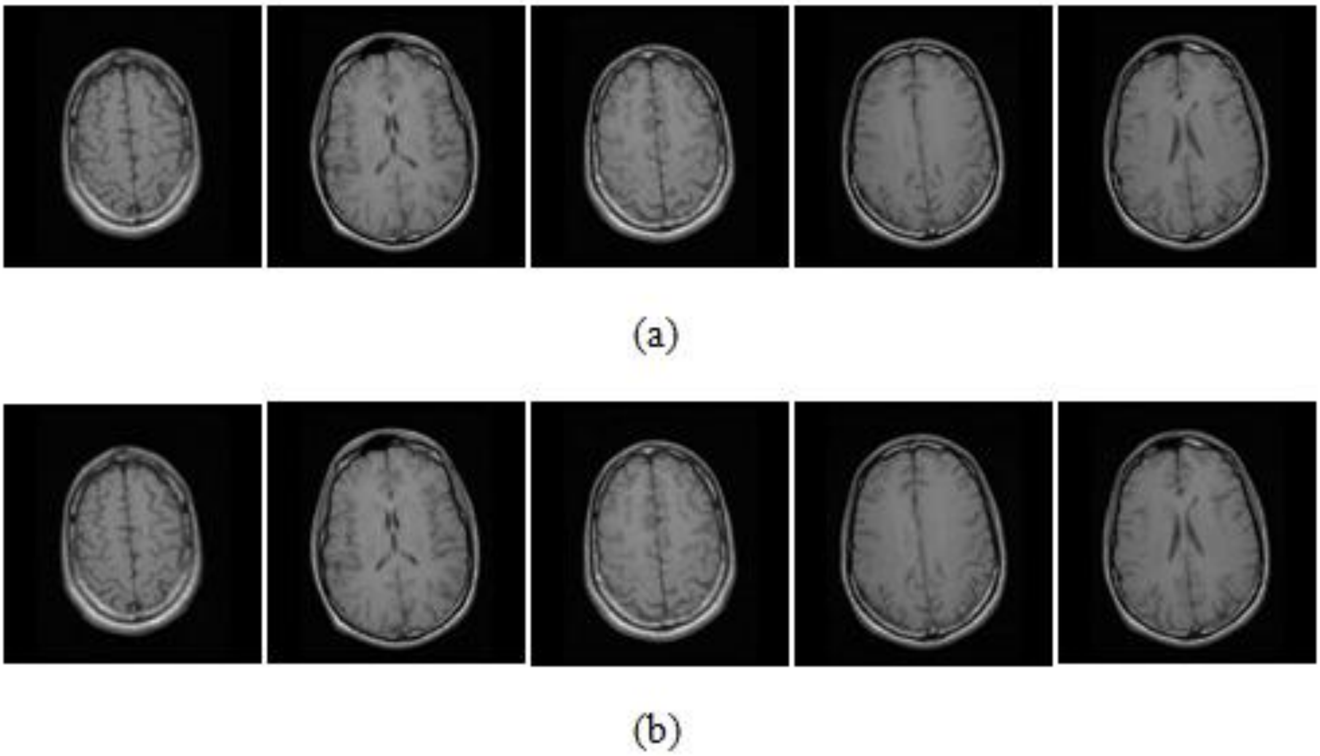

Fig 4. Sample images obtained from the compression process a) original image b) decompressed images

VI. CONCLUSION

Image compression is one of the most important applications of digital image processing. Advanced medical imaging requires storing large quantities of digitized clinical data. Due to the limited storage capacity and bandwidth, however, a medical image must be compressed before transmission and storage. FIC is a lossy image coding technique which uses the self-similarity of the image contents. A fast image compression method has been proposed, in which comparison of ranges with domains of the same image is carried out. The main disadvantage of the fractal image compression is the high encoding time. A novel fractal image compression for MRI images proposed in this paper has reduced the search and encoding time in which the expert system has employed during the encoding process, to increase the speed of encoding process without severely affecting the image quality. BPNN is used to train the expert system. Thus the proposed method reduces the encoding time by reducing the search space. The obtained experimental results clearly indicates that the performance of our Neural Network based Fractal image compression(FIC) is greatly improved in terms of encoding time without degrading the image quality compared to the usual FIC which employs exhaustive search.

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