Fractal Image Compression of Various Medical Images Using a Coherent Optimization Technique for Efficient Diagnostic Imaging Storage

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ABSTRACT

Nowadays, hospitals create more number of medical data's due to serious disease issues. Each and every application uses images in the form of data. But, images are not directly used in some applications, because of need of large amount of memory space to store images. So, it is important to compress the medical images for storage and communication purpose. Compression is one of the essential techniques to solve the increase demands in storage space. To compress the medical images, various techniques have been used. Many compression methods give high compression ratio with loss of quality of image. Medical images should always be stored in lossless format. There are several lossless compression techniques using which, original images can be restored. The main goal of image compression is a depletion of unrelated and redundant information from the original data. Different compression algorithms are currently used in medical imaging, one such type of image compression is Fractal Image Compression (FIC). These FIC techniques commonly use the optimization techniques to find the optimal best solution. It produces high compression ratio, fast decompression in short amount of time. In this paper, Flower Pollination Based Optimization approach is used for fractal image compression of various medical images. This optimization technique effectively reduces the encoding time while retaining the quality of the medical images. Here, Flower pollination algorithm (FPA) is compared with Genetic algorithm(GA) and their performances are evaluated in terms of compression ratio, encoding and decoding time and PSNR(Peak Signal to Noise Ratio) value.

I. INTRODUCTION

Compression and decompression technology of medical images has become an important aspect in the storing and transferring of medical images in information society. Most of the methods in use can be classified under the head of lossy compression. This implies that the reconstructed image is always an approximation of the original image. Fractal image coding introduced by Barnsley and Jacquin [1&2] is the outcome of the study of the iterated function system developed in the last decade. Because of its high compression ratio and simple decompression method, many researchers have done a lot of research on it. But the main drawback of their work can be related to large computational time for image compression. The first practical fractal image compression scheme was introduced in 1992 by Jacquin. One of the main disadvantages of using exhaustive search strategy is the low encoding speed.

Medical images are a special category of images because of their characteristics and purposes. These are generally obtained from special equipments, such as computed tomography (CT), magnetic resonance (MRI), ultrasound (US), X-ray diffraction, electrocardiogram (ECG), and positron emission tomography (PET). Since storage space demands in hospitals are continually increasing, compression of the recorded medical images is required. Compression is the process of coding that will effectively reduce the total number of bits needed to represent certain information. Compression consists of encoding and decoding process. Also, there are two types of image compression which is lossy compression and lossless compression. There is a need for both lossy and lossless image compression in order to store and transmit the medical images without affecting originality. Lossless Compression techniques, preserves all the needed relevant and important image information. Whereas, Lossy Compression techniques are more efficient in terms of storage and transmission needs, but there is no guarantee that they can preserve the characteristics needed in medical image processing and diagnosis.

Fractal compression is a lossy compression method for medical images, based on fractals. The aim of the FIC is to divide the medical image taken into pieces or sections and then finds self-similar ones. The method is best suited for textures and medical images, relying on the fact that parts of an image often resemble other parts of the same image. Fractal image compression is attractive because of high compression ratio, fast decompression and multi-resolution properties. The two major advantages of changing images to fractal data are, 1) the memory size required to store fractal codes is extremely smaller than the memory required to store the original bitmap information, 2) the image can be scaled up or down a size (zooming) easily without disrupting the image details as the data becomes mathematical on conversion of image to fractals [3]. In FIC, encoding process is more time consuming than decoding. Lately, many researchers have looked into a fast encoding algorithm to speed-up the fractal encoding process [4].To overcome this drawback, many optimization algorithms [5,6] such as Genetic Algorithm, Flower Pollination Algorithm, etc were introduced and used.

In the present work, Flower pollination algorithm is compared with Genetic algorithm. This paper will describe how the performance of flower pollination algorithm is better compared to Genetic algorithm for different medical images.

GAs are member of a wider population of algorithm, Evolutionary Algorithm (EA). The idea of evolutionary computing was introduced in the year 1960 by I. Rechenberg in his work “evolution strategies” (“Evolutions strategie” in original). Genetic Algorithm (GA) was invented by John Holland. Genetic algorithms (GA’s) are a stochastic global search method that mimics the process of natural evolution. Instead of searching one point at a time, GA’s use multiple search points. Thus, GA’s can claim significant advantage of large reduction in search space and time. A few investigations have been carried out in application of GA to fractal image compression. GA is an efficient means of investigating large combinational problems. But it also suffers from major disadvantages such as, it is computationally expensive, sensitive to initial parameters and not guaranteed to find an optimal solution. To overcome these disadvantages, this paper uses Flower Pollination algorithm (FPA).

The latest nature inspired algorithm is Flower Pollination Algorithm which was proposed by Xin-She Yang in 2012 [5]. This is based on the pollination of flowers. Flower Pollination Based Optimization is nature inspired algorithm which decreases the search complexity of matching between range block and domain block. Also, the optimization technique has effectively reduced the encoding time while retaining the quality of the image. Flower pollination is a process associated with transferring flowers pollens. The main actors of performing such transfer are birds, bats, insects, and other animals. There exist some flowers and insects that have made what we can call a flower-pollinator partnership. These flowers can only attract the birds that are involved in that partnership, and these insects are considered the main pollinators for these flowers. The pollination is a result of fertilization and it is must in agriculture to produce fruits and seeds [6]. Flower pollination process can occur at both local and global levels. Flower pollination process is achieved through cross-pollination or self-pollination.

II. FRACTAL IMAGE COMPRESSION

Iteration Function System (IFS) is the basic idea of fractal image compression in which the governing theorems are the Collage Theorem and the Contractive Mapping Fixed-Point Theorem [7]. The encoding unit of FIC for given grey level image of size N x N is (N/L)2 of non-overlapping range blocks of size L x L which forms the range pool *R*. For each range block *v* in *R,* one search in the (N - 2L + 1)2 overlapping domain blocks of size 2L x 2L which forms the domain pool *D* to find the best match. The parameters describing this fractal affine transformation of domain block into range block form the fractal compression code of *v*. The parameters of fractal affine transformation is *Φ* of domain block into range block having domain block coordinates (t_x, t_y)*,* Dihedral transformation-*d,* contrast scaling-*p,* brightness offset-*q.*

$$\Phi\begin{bmatrix} x \\ y \\ u(x,y) \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} & 0 \\ a_{21} & a_{22} & 0 \\ 0 & 0 & p \end{bmatrix}\begin{bmatrix} x \\ y \\ u(x,y) \end{bmatrix} + \begin{bmatrix} t_x \\ t_y \\ q \end{bmatrix}, \qquad (1)$$

Where the 2 x 2 sub-matrix $\begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}$ is one of the Dihedral transformations in (2)

$T_0 = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$, $T_1 = \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}$, $T_2 = \begin{bmatrix} -1 & 0 \\ 0 & 1 \end{bmatrix}$, $T_3 = \begin{bmatrix} -1 & 0 \\ 0 & -1 \end{bmatrix}$,

$T_4 = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}$, $T_5 = \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix}$, $T_6 = \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix}$, $T_7 = \begin{bmatrix} 0 & -1 \\ -1 & 0 \end{bmatrix}$. (2)

The above parameters are found using the following procedure,
1. The domain block is first down-sampled to L x L and denoted by *u.*

2. The down-sampled block is transformed subject to the eight transformations T_k: k = 0,. . . ,7 in the Dihedral on the pixel positions and are denoted by u_k, k = 0,1, . . . ,7, where $u_0 = u$. The transformations *T*1 and *T*2 correspond to the flips of *u* along the horizontal and vertical lines, respectively. *T*3 is the flip along both the horizontal and vertical lines. *T*4, *T*5, *T*6, and *T*7 are the transformations of *T*0, *T*1, *T*2, and *T*3 performed by an additional flip along the main diagonal line, respectively.

3. For each domain block, there are eight separate MSE computations required to find the index d such that,

The eight transformed blocks are denoted by $u_{k,}$ k = 0,1, . . . ,7, where u_0 = u. The transformations T1 and T2 correspond to the flips of u along the horizontal and vertical lines, respectively. T3 is the flip along both the horizontal and vertical lines. T4, T5, T6, and T7 are the transformations of T0, T1, T2, and T3 performed by an additional flip along the main diagonal line, respectively. In fractal coding, it is also allowed a contrast scaling p and a brightness offset q on the transformed blocks. Thus, the fractal affine transformation U of u(x,y) in D can be expressed as

$$d = \arg\min\{\mathrm{MSE}((p_k u_k + q_k), v): k = 0,1,\ldots.,7\} \quad (3)$$

where $$\mathrm{MSE}(u,v) = \frac{1}{L^2}\sum_{i,j=0}^{L-1}(u(i,j=0) - v(i,j))^2 \quad (4)$$

Here, $p_k$and $q_k$can be computed directly as

$$p_k = \frac{\left[L^2\{u_{k,}, v\} - \sum_{i=0}^{L-1}\sum_{j=0}^{L-1} u_k(i,j)\sum_{i=0}^{L-1}\sum_{i=0}^{L-1} v(i,j)\right]}{\left[L^2(u_k, u_k) - \left(\sum_{i=0}^{L-1}\sum_{j=0}^{L-1} u_k(i,j)\right)^2\right]} \quad (5)$$

$$q_k = \frac{1}{L^2}\left[\sum_{i=0}^{L-1}\sum_{i=0}^{L-1} v(i,j) - p_k\sum_{i=0}^{L-1}\sum_{j=0}^{L-1} u_k(i,j)\right] \quad (6)$$

4. As *u* runs over all of the domain blocks in *D* to find the best match, the terms t_x and t_y can be obtained together with *d* and the specific *p* and *q* corresponding this *d*, the affine transformation (1) is found for the given range block *v*.

To decode, the compression codes to obtain a new image, and proceeds recursively by chooses any image as the initial one and makes up the (N/L) 2 affine transformations. According to Partitioned Iteration Function Theorem (PIFS), the sequence of images will converge. The final image is the retrieved image of fractal coding.

III. GENETIC ALGORITHM OPERATION

Genetic Algorithms (GAs) are adaptive heuristic search algorithm depends on the evolutionary ideas of natural selection and genetics. The searching process used by genetic algorithm is similar to that in nature, where successive generations of organisms are reproduced and raised until they themselves can reproduce. To use a genetic algorithm, initialize the genetic algorithm with a set of solutions represented by chromosomes called a population. Each solution can be represented as either real valued numbers or a binary string of ones and zeros. These solutions are known as individuals. In these algorithms the fittest among a group of individuals survive and are used to form new generations of individuals with improved fitness vales. The fitness of an individual is a measure of how well the individual has performed in the problem domain.

To illustrate the working process of genetic algorithm, the steps to realise a basic GA
are listed:

Step 1: Represent the problem variable domain as a chromosome of fixed length; choose the size of the chromosome population N, the crossover probability Pc and the mutation probability Pm.
Step 2: Define a fitness function to measure the performance of an individual chromosome in the problem domain. The fitness function establishes the basis for selecting chromosomes that will be mated during reproduction.
Step 3: Randomly generate an initial population of size N: x , x ,..., xN 1 2
Step 4: Calculate the fitness of each individual chromosome: ( ), ( ),..., ( ) 1 2 $N f x f x f x$
Step 5: Select a pair of chromosomes for mating from the current population. Parent chromosomes are selected with a probability related to their fitness. High fit chromosomes have a higher probability of being selected for mating than less fit chromosomes.
Step 6: Create a pair of offspring chromosomes by applying the genetic operators.
Step 7: Place the created offspring chromosomes in the new population.
Step 8: Repeat Step 5 until the size of the new population equals that of initial population, N.
Step 9: Replace the initial (parent) chromosome population with the new (offspring) population.
Step 10: Go to Step 4, and repeat the process until the termination criterion is satisfied.
A GA is an iterative process. Each iteration is called a generation. A typical number of generations for a simple GA can range from 50 to over 500. A common practice is to terminate a GA after a specified number of generations and then examine the best chromosomes in the population. If no satisfactory solution is found, then the GA is restarted .

IV. FLOWER POLLINATION ALGORITHM

Pollination is a process of transfer of pollen from the male parts of a flower called another to the female part called stigma of a flower. The reproduction in plants happens by union of the gametes. The pollen grains produced by male gametes and ovules borne by female gametes are produced by different parts and it is essential that the pollen has to be transferred to the stigma for the union. This process of transfer and deposition of pollen grains from anther to the stigma of flower is pollination. The process of pollination is mostly facilitated by an agent.

The flower pollination algorithm, inspired by the flow pollination process of flowering plants. The FPA has been extended to multi-objective optimization. For simplicity, the following four rules are used.
(1)Biotic cross-pollination can be considered as a process of global pollination, and pollen carrying pollinators move in a way that obeys Lévy flights (Rule 1).

(2)For local pollination, abiotic pollination and self-pollination are used(Rule2).

(3)Pollinators such as insects can develop flower constancy, which is equivalent to a reproduction probability that is proportional to the similarity of two flowers involved (Rule 3).

(4)The interaction or switching of local pollination and global pollination can be controlled by a switch probability p in [0, 1], slightly biased towards local pollination (Rule 4).

To formulate the updating formulas, these rules have to be changed into correct updating equations. The main steps of FPA, or simply the flower algorithm are illustrated below:

min or max objective *f(x), x = (x1, x2 , . . . , xd)*
Initialize n flowers or pollen gametes population with random solutions
Identify the best solution (g*) in the initial population
Express a switch probability p in [0, 1]
While (t < Max Generation)
for i = 1 : n (all n flowers in the population)
if rand < p,
Draw a (d-dimensional) step vector L *from a* Levy distribution
Global pollination via $X_i^{t+1} = X_i^t + \gamma L \ (g^* - X_i^t)$,
else
Draw ∈ from a uniform distribution in [0,1]
Do local pollination via

$X_i^{t+1} = X_i^t + \in (X_j^t - X_k^t)$,
end if
Evaluate new solutions
If new solutions are better, update them in population
end for
Find current best solution
end while
Output the best solution obtained

In principle, flower pollination process can happen at both local and global levels. But in reality, flowers in the neighbourhood have higher chances of getting pollinated by pollen from local flowers than those which are far away.

To simulate this feature, a proximity probability p (Rule 4) can be commendably used to switch between intensive local pollination to common global pollination.

V. RESULTS AND DISCUSSIONS

In the present work, the Flower pollination algorithm is compared with Genetic algorithm for various medical images. GA and FPA are implemented and executed on MATLAB. The FPA has advantages such as simplicity and flexibility. In terms of number of parameters, the FPA has only one key parameter *p* together with a scaling factor *γ*, which makes the algorithm easier to implement.

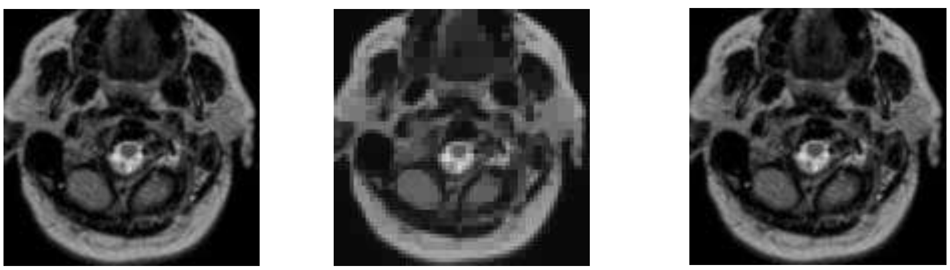

Fig.5.1(a) Original MR image1 (b) Decompressed image1 using GA (c) Decompressed image1 using FPA

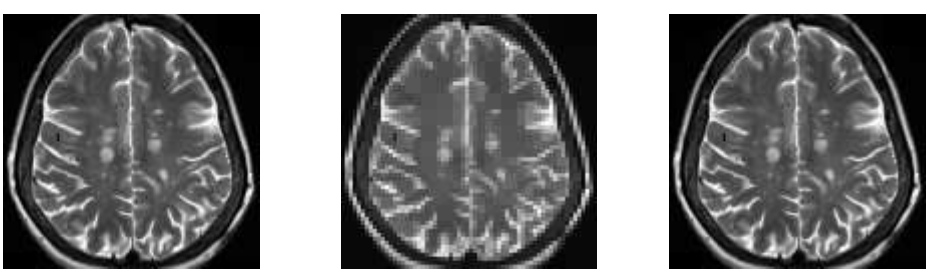

Fig.5.2(a) Original MR image2 (b) Decompressed image2 using GA (c) Decompressed image2 using FPA

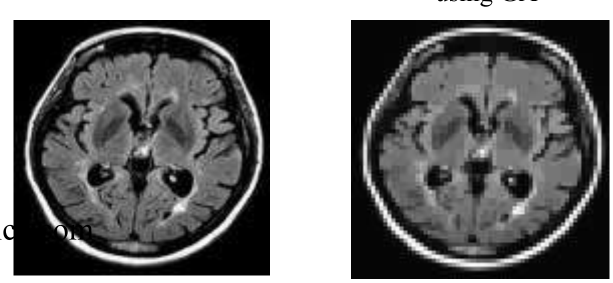

Fig.5.3(a) Original MR image3 (b) Decompressed image3 using GA (c) Decompressed image3 using FPA

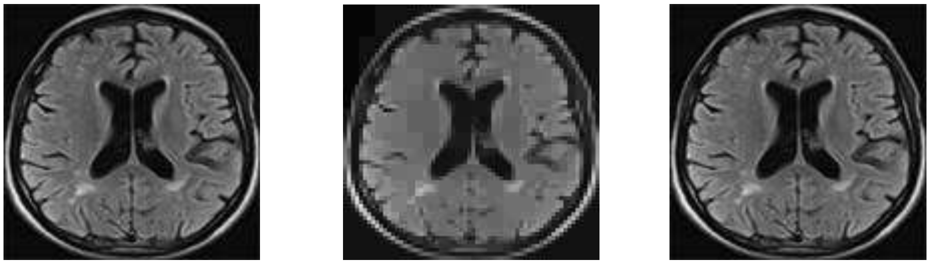

Fig.5.4(a) Original MR image4 (b) Decompressed image4 using GA (c) Decompressed image4 using FPA

The figures of 5.1, 5.2, 5.3, 5.4 shows the original MR images, compressed images and decompressed images using both Genetic Algorithm and Flower Pollination Algorithm. The above figures describes that decompressed FPA MR images has better visual quality than decompressed GA MR images. Results shows that FPA could perform better than GA. In terms of perfomance, FPA retains the quality of the image. According to iteration and population size, both GA and FPA algorithms are evaluated for various medical images. The number of iterations is set equal to 20. The size of the population usually remains fixed in any metaheuristic approach. Generally GA gives near optimal solutions. But, Image compressed using FPA is much close to original one, eliminating distortion of the image in FIC.

FPA has the ability to solve continuous optimization problems. The results are evaluated by standard compression metrics like Peak Signal Noise Ratio (PSNR), Compression Ratio (CR) and Compression Time (CT). PSNR is used to evaluate the quality between the compressed or reconstructed image and the original image. PSNR value is generally measured in decibels.

$$\text{PSNR} = 20\, log_{10} \frac{255}{\sqrt{MSE}}$$

Compression efficiency is measured by compression ratio.

Where,

$$\text{CR} = \frac{\text{Original image size}}{\text{Compressed image size}}$$

The performance analysis of GA and PSO is presented in Table 1 for four different medical images.

TABLE 1 Comparison results of GA and FPA for four different MR images

Compression Method	MR Image 1		MR Image 2		MR Image 3		MR Image 4	
	GA	FPA	GA	FPA	GA	FPA	GA	FPA
Population size	20	20	20	20	20	20	20	20
Iteration	100	100	100	100	100	100	100	100
PSNR	13.937043	27.223524	11.554783	22.407242	10.067954	21.624371	12.156697	23.878259
Compression time (s)	77.223243	62.113868	83.916275	71.321329	79.690432	66.559429	76.898554	62.748786

Decompression time (s)	45.453204	28.184911	57.873612	45.953484	65.997641	50.347582	49.790571	35.840365
Compression ratio	5.3403686	9.977696	3.894732	8.057168	4.578011	8.303842	5.894463	9.322333

From simulation results, we can see that the FPA gives a very good PSNR values, compression time and compression ratio for MR images 1,2,3&4. The above results proves that the accuracy and speed performance of FPA is better than GA. The increased PSNR value indicates that FPA performs better than GA. Computation time is minimized using FPA which indicates its efficiency. Without compromising quality, FPA gives high compression ratio. Thus, FPA is reliable and efficient at finding global optimal solution when compared to GA. Additionally, this paper specifies that the FPA technique is better suited for applications requiring fast access to high quality images.

VI. CONCLUSION

Compression is important for some multimedia and online applications. We can get good quality decoded image with significant amount of compression.. Usually a decoded image should have very high PSNR value to have a better quality. In this paper, Flower Pollination Based Optimization approach is used for fractal image compression of various medical images. This image compression algorithm is very efficient in terms of compression ratio and compression time and also, it retains the quality of image in terms of better PSNR value. FPA can be used for solving both single objective and multiobjective optimization problems. Simulation results and tabulation have shown that the Flower Pollination algorithm for medical images is very efficient compared to Genetic algorithm. Overall performance of FPA is better. FPA looks very promising and is still in budding stage and can be applied for medical image analysis and in other area of researches.

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