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## FRACTAL IMAGE COMPRESSION OF MEDICAL IMAGE USING EFFICIENT OPTIMIZATION TECHNIQUE

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**Abstract:** *Medical images play a vital role in the area of medicine. It is important to store the medical images for future reference. So, there is a need for compressing of medical images for storage and communication purpose. Over the last few decades, many image compression methods have been introduced. They 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 objective of image compression is to reduce the redundancy of the image and to store or transmit data in an efficient form. The different compression algorithm currently in use 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. The aim of the FIC is to divide the image into pieces or sections and then finds self-similar ones. 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. This optimization technique effectively reduces the encoding time while retaining the quality of the image. Here, Flower pollination algorithm (FPA) is compared with Genetic algorithm (GA) and their performances are analyzed in terms of compression ratio, encoding time and Peak Signal to Noise Ratio (PSNR).*

**Keywords:** *Fractal image compression, medical image, flower pollination algorithm*

### 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 [1-3] 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.

The advent of the digital department has resulted in a growing number of digital images, particularly as a result of magnetic resonance imaging (MRI) and multislice computed tomography (CT). To effectively deal with the growing size of digital examination files, compression is required for distribution.

Medical Image Compression is very important in the present world for efficient archiving and transmission of images. Compression is the process of coding that will effectively reduce the total number of bits needed to represent certain information. Basically, two types of compression are available. (i) Lossy Compression (ii) Lossless Compression.

(i) Lossy Compression: In this compression there is loss of information and the original image is not recovered exactly. This is irreversible. Most lossy data compression

formats suffer from generation loss: repeatedly compressing and decompressing the file cause it to progressively loss quality.

(ii) Lossless Compression: The aim of lossless image compression is to represent an image signed with the smallest possible number of bits without losing any of the information, thus it speeds up transmission and minimizes storage requirement. This reproduces the original image without any quality loss. This is irreversible. This contains two steps. When large amount of data is transferred through the network the bandwidth gets wasted. To avoid that lossless compression techniques are used to reduce the storage space [4].

Fractal compression is a lossy compression method for medical images, based on fractals. 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 bit map 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 [7]. 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 [8]. To overcome this drawback, many optimization algorithms such as Genetic Algorithm, Flower Pollination Algorithm 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 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 strategies” 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 [9]. 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 [10]. 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 [11]. The encoding unit of FIC for given grey level image of size N x N is (N/L)<sup>2</sup> 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)<sup>2</sup> 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 Dihedral transformation-d, contrast scaling-p, brightness offset-q.

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

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)

$$\begin{aligned} T_0 &= \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, T_1 = \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}, T_2 = \begin{bmatrix} -1 & 0 \\ 0 & 1 \end{bmatrix}, T_3 = \begin{bmatrix} -1 & 0 \\ 0 & -1 \end{bmatrix}, \\ T_4 &= \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}, T_5 = \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix}, T_6 = \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix}, T_7 = \begin{bmatrix} 0 & -1 \\ -1 & 0 \end{bmatrix}. \end{aligned}$$

The above parameters are found using the following procedure,

1. The domain block is first down-sampled to  $L \times L$  and denoted by  $u$ .

2. The down-sampled block is transformed subject to the eight transformations :  $k = 0, \dots, 7$  in the Dihedral on the pixel positions and are denoted by  $u_k, k = 0, 1, \dots, 7$ , 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.

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  $u_k, k = 0, 1, \dots, 7$ , 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

$$d = \operatorname{argmin}\{MSE((p_k u_k + q_k), v) : k = 0, 1, \dots, 7\} \quad (3)$$

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

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

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

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

4. As  $u$  runs over all of the domain blocks in  $D$  to find the best match, the terms  $p_k$  and  $q_k$  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

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 realize 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  $P_c$  and the mutation probability  $P_m$ .

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  $N$ :  $x_1, x_2, \dots, x_N$

Step 4: Calculate the fitness of each individual chromosome:  $f(x_1), f(x_2), \dots, f(x_N)$

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.

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

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  $f(x)$ ,  $x = (x_1, x_2, \dots, x_d)$

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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 ( $t < \text{Max Generation}$ )
  for  $i = 1 : n$  (all n flowers in the population)
    ifrand  $< p$ ,
      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  $\epsilon$  from a uniform distribution in  $[0,1]$ 
      Do local pollination via
       $X_i^{(t+1)} = X_i^{(t)} + \epsilon(X_j^{(t)} - X_k^{(t)})$ ,
    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 medical image. 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  $\gamma$ , which makes the algorithm easier to implement.



(a)



(b)



(c)

Figure 1. (a): Original Image (b): Decoded GA MR image (c): Decoded FPA MR image

The figures of 1(a),5(b),5(c) shows the original image, the decoded GA image and the decoded FPA image. These figures shows that that the decoded FPA image has better quality than the decoded GA image. The decoded FPA image gives better quality with the increase in number of iterations. The numeric results containing encoding time and PSNR value of decoded MR images are given in table. From simulation results, we see that the FPA gives a very good PSNR values, compression time and compression ratio for MR image. The visual quality of the decoded FPA MR image is good, compared to the decoded GA MR image.

**TABLE 1. COMPARISON RESULTS OF GA AND FPA FOR MR IMAGE**

COMPRESSION METHOD	GA	FPA
Population size	20	20
Iteration	100	100
PSNR	21.75424	25.8004
Compression time (s)	56.1248	43.56
Decompression time (s)	51.187	29.58
Compression ratio	4.8	8.25

**VI CONCLUSION**

With the increasing applications, higher compression ratios that are currently being used, retains the necessary information necessary. Compression is compulsory required for some applications. Fractal analysis is suitable for MR image analysis. Various researches have been done on fractal geometry in medical images. So, these approaches have been very effective and popular in recent years. In this paper, Flower Pollination Based Optimization approach is used for fractal image compression. 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 multi-objective optimization problems. Simulation results and tabulation have shown that the Flower Pollination algorithm for medical image is very efficient compared to Genetic algorithm. i.e. The increased PSNR value indicates that FPA is better. The FPA reduces time, improves the results and the performance is better compared to other optimization techniques. FPA looks very promising and is still in budding stage and can be applied for medical image analysis and in other areas of researches.

**REFERENCES**

[1] Barnsley M.F. 1988. "Fractals Everywhere". New York: Academic.  
 [2] Jacquin A.E.. (1992). "Image coding Based on a Fractal theory of Iterated contractive Image Transformations". IEEE Transactions on Image Processing, Vol. 1. pp. 18-30.

[3] Jacquin. A.E. 1993. Fractal Image coding: A Review Proc. IEEE. Vol. 81. pp. 1451-1465.  
 [4] Ghare, S.E..Mohd M.A .Ali, Jumari K.and Ismail, M (2009). "An Efficient Low Complexity Lossless Coding Algorithm for Medical Images". In American Journal of Applied Sciences 6 (8): 1502-1508.  
 [5] Jayasuriya, S.A. Liew, A.W.C.. Law N.F (2009). "Brain symmetry plane detection based on fractal analysis., Elsevier, Medical Image Analysis.  
 [6] McInness M. (2005). "Digital compression of medical images: an assessment of legal risk". Located at: Ivey School, University of Western Ontario, London, Ontario.  
 [7] Donald Walter, (2003). "Fractal and Wavelet Image Compression of Astronomical Images". URJA.  
 [8] Lifeng Xi and Liangbin Zhang, (March 2007) "A Study of Fractal Image Compression Based on an Improved Genetic Algorithm". International Journal of Nonlinear Science, Vol.3, No.2, pp. 116-124.  
 [9] Xin-She Yang, Mehmet Karamanoglu, XingshiHe, "Multi-objective Flower Algorithm for Optimization", ICCS 2013, Elsevier.  
 [10] Flower Pollination by biology. tutorvista.com /animalkingdom,Pearson,2005  
 [11] Fisher, Y. Fractal Image Compression: Theory and Application, Springer-Verlag, New York, 1994.  
 [12] Mohamed, Faraoun Kamel., Aoued, Boukeli F. (2005), "Optimization of Fractal Image Compression Based On Genetic Algorithms". 3rd International Conference: Sciences of Electronic, Technologies of Information and Telecommunications, Tunisia.  
 [13] Mitra, S.K.. Murthy, C.A. Kundu, M.K (1998). "Technique for fractal image compression using genetic algorithm". IEEE Transactions on Image Processing 7 586–593.  
 [14] Xin-She Yang, (Dec 2013) "Flower Pollination Algorithm for Global Optimization". International Conference on Unconventional Computing and Natural Computation, pp. 240-249.  
 [15] Gaganpreet Kaur Dheerendra Singh, Manjinder Kaur, "Robust and Efficient 'RGB' based Fractal Image Compression: Flower Pollination based Optimization", International Journal of Computer Applications (0975 –8887), Volume 78 – No.10, 2013.  
 [16] Abdel-Raouf, O. Abdel-Baset, M. El-henawy, I. (2014) "A New Hybrid Flower Pollination Algorithm for Solving Constrained Global Optimization Problems". International Journal of Applied Operational Research Vol. 4, No.2, pp. 1-13, Spring.