International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395 -0056
Volume: 04 Issue: 01 | Jan -2017 www.irjet.net p-ISSN: 2395-0072

Fractal Image Compression By Range Block Classification

Miss. Gauri R. Desai [1], Dr. Mahesh S. Chavan[2]

[1] *PG Student, Department of Electronics Engineering*
KIT's COE Kolhapur, Maharashtra, India
[2] *Professor, Department of Electronics Engineering*
KIT's COE Kolhapur, Maharashtra, India

---***---

Abstract - *Image compression is a technique in which we can store the huge amount of images, videos in less memory. Which will helpful to increase storage capacity and transmission performance, For the Fractal image compression lossy compression is used. Mainly the fractal image compression involves partitioning the images into Range Blocks and Domain blocks. Then each range block searches for best domain block by using particle swarm optimization Algorithm.*

Key Words: Fitness function, Fractal block coding, Image data compression, Particle swarm optimization, reduced domain block.

1. INTRODUCTION

Mainly there are two types of compression techniques namely lossy and lossless data compression. Here in fractal image compression lossy technique is used it gives the constructed image is actually an approximation of input image that is original image. Fractal image code is implemented by Barnsley and Jacquin. The main advantage of fractal image compression it gives high data compression ratio, and less decompression time. But the main disadvantage with this technique is large encoding time for image data compression. At present in this paper we have focused on enhancing the data compression ratio and improves the image quality after the decompression. Fractal means the geometrical figure obtained by partitioning the original image into range blocks and domain blocks then each range block finds the best matching domain block iteratively by using particle swarm optimization algorithm.

Particle swarm optimization algorithm is mainly population based algorithm. Introduced by Kennedy & Eberhart in 1995. Inspired by social behavior of birds and fish. All the particles searches for the best result. If one of the particle finds the best results then remaining all will follow the same. Every particle has own memory, it searches for best matched range block with domain block iteratively by self-similar property.

2. PARTICLE SWARM OPTIMIZATION ALGORITHM

Particle swarm optimization algorithm is population based algorithm introduced by Kennedy and Eberhart in 1995. PSO idea emerged from group of birds, schools of fish, or swarm of bees. As it is population based method solves various function optimization problems. When the swarm of birds searches for food in different places ,if anyone has found the food then remaining all will follow to that bird for food this idea is implemented for particle swarm optimization here swarm of birds means the swarm of particles, each particle has its own position and velocity. Individual particle searches for best optimization solution that is called position best solution (pbest). Again the particle update its position and velocity for best results. Particle every time update its position and velocity iteratively and final optimization result called as Gbest.

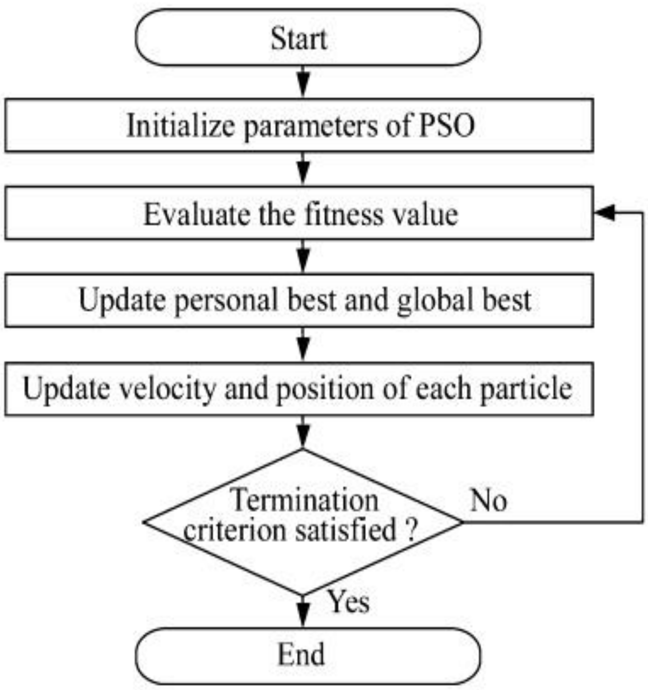

Fig- 1: PSO Algorithm

3. IMPLEMENTATION OF FRACTAL IMAGE COMPRESSION USING PSO ALGORITHM

Input original image in gray scale and create R pool by partitioning original image into non-overlapping R sub blocks of size 8 × 8. Create D block by partition image into overlapping D sub blocks of size 16 × 16.The whole D blocks are contracted into blocks of size 8 × 8 by averaging four pixel values to one pixel value. Compute standard deviation σ of each block by equation

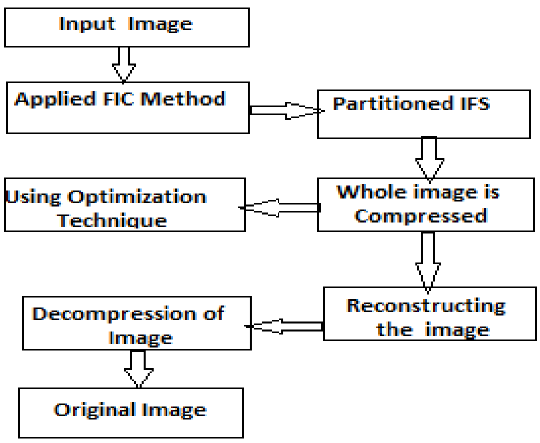

Fig -2: Block diagram for proposed system

$$\sigma R = \frac{(\ ||| R - R \times I |||\ )}{\sqrt{n}} \ldots\ldots\ldots\ldots\ldots(1)$$

Let T is the threshold value which divides the R blocks into Rs and Rn

$$R = \begin{cases} R\ s, if\ \sigma \leq T \\ Rn, if\ \sigma \geq T \end{cases} \ldots\ldots\ldots\ldots(2)$$

The Rs block employs its average pixel value instead of the information of the best matched D block as the fractal Codes. For the Rn blocks, a PSO strategy is proposed. Firstly, initialize the particle swarm size and the particles. Every particle is encoded as (x, y) randomly and (x, y) is the location of the D block in the {D}. Secondly, all R blocks search the best matched D blocks in the swarm successively. Each particle (x, y) finds the D block at (x, y) in the image, zooms the D block in the same size of R block and extends it with eight symmetrical transformations when seeking in the particle swarm. Then compute the fitness value which is defined as the minimal E(R , D), and record the corresponding fractal codes. Each R block performs the procedure iteratively, and if required update the pbest, gbest and fractal codes. Thirdly, if all the R blocks have found the best matched D blocks, then stop. Rn blocks adopt the PSO as the block searching mechanism instead of the traditional full search method, which improves the encoding time.

3.1 Partitioned image into R and D blocks

Fractal image block-coding compression methods compress data by partitioning the data into range blocks, and also into domain blocks. For each range block, the method searches a best matching domain block that can be transformed into the range block. It focus on using sophisticated deformations to best transform a given domain block into a given range block. Consider original grayscale image is of size m × m. Let the range block R be defined as all non-overlapping partitions of size n × n of the image f, which makes up (m/n) 2 blocks.

Let the domain blocks D be defined as the group of all possible blocks of size 2n × 2n of the image f, which makes up (m - 2n + 1)2 blocks. For m is 256 and n is 8, the range blocks R is composed of (256/8) × (256/8) = 1024 blocks of size 8 × 8 and the domain block D is of ((256 - 16 + 1) × (256 - 16 + 1) = 58081 blocks of size 16 × 16. For each range block v from the R, in the fractal affine transformation is obtained by searching all of the domain blocks in the D to find the most matching one and the parameters representing the fractal affine transformation will form the fractal compression code for v. To execute the similarity matching measure between range block and domain block, in the size of the domain block must be first

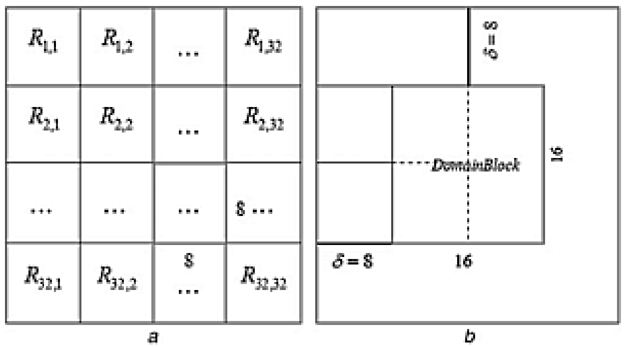

Fig -3: Range and Domain Blocks

Sub-sampled to 8 × 8 such that its size is the same as the range block. The arrangements of R and D blocks. Finally, the D blocks after averaging the pixel values are extended with eight symmetrical transformations (identity T0, 90° clockwise rotation T, 180° clockwise rotation T2, 270° clockwise rotation T3, x reflection T4, y reflection T5, y = x reflection T6and y = -x reflection T7)

4. EXPERIMENTAL RESULTS

The proposed algorithm has been applied and tested with some Bitmap images. Four Bitmap images of dimension 256 x 256 presented are chosen to demonstrate our results. The input image is converted into gray scale and then divided into 8x8 blocks called ranges and 16x16 blocks called domain blocks, each of which is encoded separately.

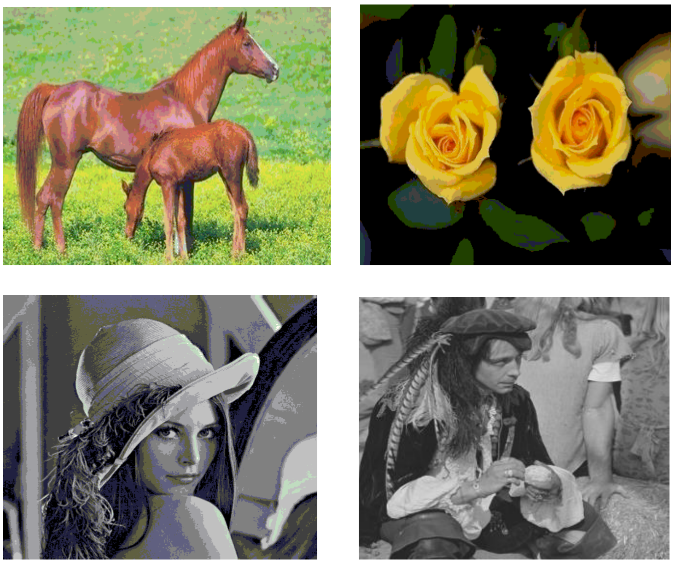

Fig-4: Test Images

When we select the bitmap image as a test image that converted into gray scale image and resizes into 512×512.

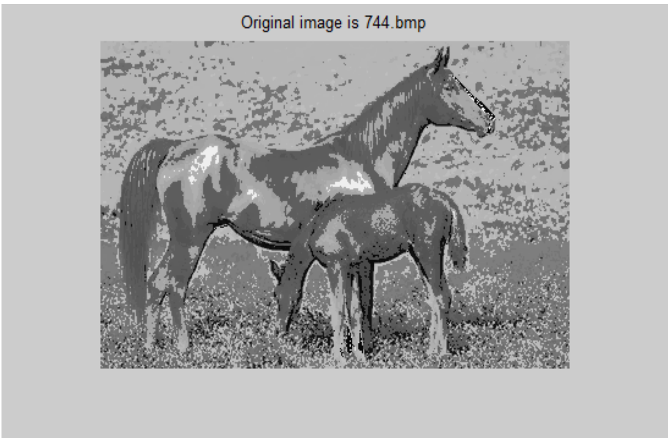

Fig-5: Original Gray scale Images

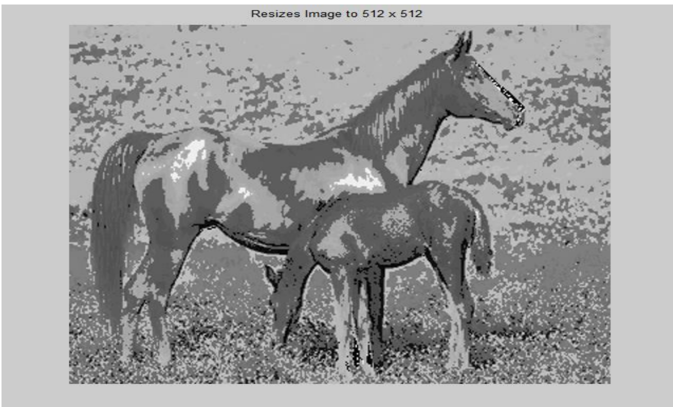

Fig-6: Resized Image

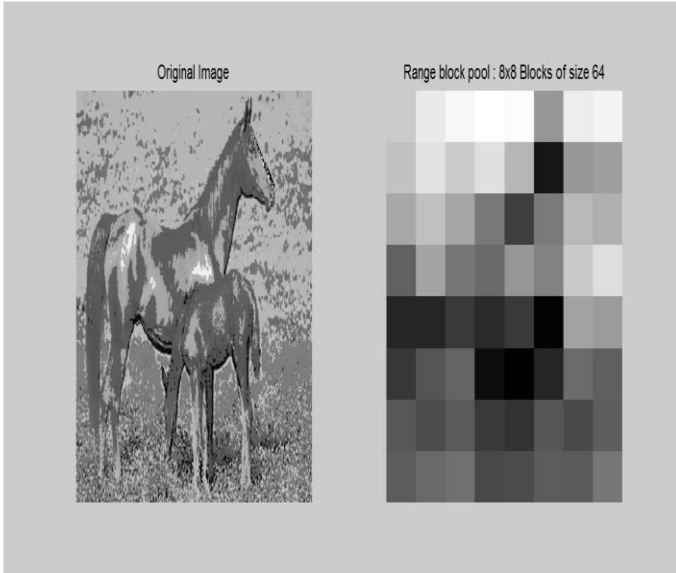

Fig-7 : Test image portioned into range and domain blocks.

REFERENCES

1. M.F. Barnsley, "Fractal Everywhere," Academic, New York, 1988.
2. A.E. Jacquin, "Image coding based on a fractal theory of iterated contractive image transformations," IEEE Transactions on Signal Processing, vol. 1, pp. 18-30, 1992.
3. Y. Fisher, "Fractal Image Compression," Theory and Application, Springer Verlag, Berlin, 1995.
4. Z. Wang, D. Zhang, Y. Yu, "Hybrid image coding based on partial fractal mapping," Signal Process. Image Commun, vol. 15, no. 9, pp. 767-769, 2000.
5. T.K. Truong, C.M. Kung, J.H. Jeng, M.L. Hsieh, "Fast fractal image compression using spatial correlation," Chaos, Solitons and Fractals, vol. 22, pp. 1071-1076, 2004.
6. Li, D. Yuan, Q. Xie, C. Zhang, "Fractal Image Compression by Ant Colony Algorithm," In: Proceedings of the 9th International Conference for Young Computer Scientists, IEEE, pp. 1890-94, 2008.
7. F. MOHAMED, B. AOUED, "Speeding Up Fractal Image Compression by Genetic Algorithms," Multidimensional Systems and Signal Processing, vol.16, pp. 217-236, 2005.
8. Y. Iano, F. Silvestre , A. L. Mendes Cruz, "A Fast and Efficient Hybrid Fractal-Wavelet Image Coder," IEEE TRANSACTIONS ON IMAGE PROCESSING, vol.15, no.1, pp. 98-105, 2006.
9. M. S. Wu, J. H. Jeng, J. G. Hsieh, "Schema genetic algorithm for fractal image compression," Engineering Applications of Artificial Intelligence, vol. 20, pp. 531-538, 2007.

10. M. S. Wu , W. C. Teng, J. H. Jeng, J. G. Hsieh, "Spatial correlation genetic algorithm for fractal image compression", Chaos, Solitons and Fractals, vol. 28, pp. 497-510, 2006.
11. J. Kennedy, R.C. Eberhart, "Particle swarm optimization, " in: Proceedings of IEEE International Conference on Neural Networks, Perth, Australia, vol. 4, pp. 1942–1948, 1995.
12. R.C. Eberhart, J. Kennedy, "A new optimizer using particle swarm theory," in: Proceedings of IEEE International Symposium on Micro Machine and Human Science, Nagoya, Japan, pp. 39–43, 1995.
13. C. C. Tseng, J. G. Hsieh , J. H. Jeng, "Fractal image compressionusing visual-based particle swarm optimization", Image and Vision Computing, vol. 26, pp. 1154-1162, 2008.
14. F. Bergh, A. P. Engelbrecht, "A study of particle swarm optimization particle trajectories," Information Sciences, vol. 17, no. 8, pp. 937-71, 2006.
15. X. Tang , L. Zhuang, J. Cai, C. Li, "Multi-fault classification based on support vector machine trained by chaos particle swarm optimization," Knowledge-Based Systems, vol. 23, pp. 486-490, 2010.
16. Y. Wang, J.H. Liu , "Chaotic particle swarm optimization for assembly sequence planning," Robotics and Computer-Integrated Manufacturing, vol. 26, pp. 212-222, 2010.
17. W. Xing-yuan, L. Fan-ping, W. Shu-guo, "Fractal image compression based on spatial correlation and hybrid genetic algorithm," Journal of Visual Communication and Image Representation, vol. 20, pp. 505-510, 2009.