Fast Search Fractal Image Compression Using PSO Based Optimization Technique

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ABSTRACT
In traditional fractal image compression, the encoding procedure is time-consuming due to the full search mechanism. In order to speed up the encoder, we adopt particle swarm optimization method performed under classification and Dihedral transformation to further decrease the amount of MSE computations. The classifier partitions all of the blocks in domain pool and range pool into three classes according to the third level wavelet coefficients. Each range block searches the most similar block only from the blocks of the same class. Furthermore, according to the property of Dihedral transformation, only four transformations for each domain block are considered so as to reduce the encoding time. Experimental results show that, the encoding time of the proposed method is faster than that of the full search method. Experimental results show that the proposed method is about 181 times faster with only 1.56dB decay in image quality.

Keywords
Fractal image compression, particle swarm optimization, Dihedral transformation, Encoding time.

1. INTRODUCTION

The idea of the image redundancies can be efficiently exploited by means of block self-affine transformations may call the fractal image compression (FIC), based on the partitioned iteration function system (PIFS) which utilized the self-similarity on first practical fractal image compression scheme was introduced in 1992 by Jacquin[1]. The fractal transform for image compression was introduced in 1985 by Barnsley and Demko. The very high encoding time is the main disadvantages because of exhaustive search strategy. Therefore, decreasing the encoding time is an interesting research topic for FIC.

One way of decreasing the encoding time is by using stochastic optimization methods using Genetic Algorithm (GA) this recent topics of GA-based methods are proposed to improve the efficiency [2]. The idea of special correlation of an image is used in these methods while the chromosomes in GA consist of all range blocks which leads to high encoding speed[3].

Other researchers focused on improvements by tree structure search methods of the search process and parallel search methods [4, 5] or quad tree partitioning of range blocks to make it faster.

Wavelet transform is used to decompose the original image to various frequency sub bands in which the attributes can be extracted from the wavelet coefficients belonging to different sub-bands. The distribution of wavelet coefficients can be used in context based multiscale classification of document image[6]. The fast and efficient algorithm[7] was applied to triangular mesh to approximate surface data using wavelet transform coefficients. It directly determined local area complexity in an image and divides square cells depending on complexity. In implemented a hybrid image classification method combining wavelet transform, rough set approach, and artificial neural network. Zou and Li have proposed image classification using wavelet coefficients in low-pass bands [8]. This approach was based on the distribution of histograms of the wavelet coefficients.

In this paper, it use particle swarm optimization method to reduce the search space for FIC[11]. If the two blocks are not of the same type no similarity will not be calculated. The classification method is to partition all of the blocks in domain pool and range pool into three classes according to third level wavelet coefficients. Each range block calculates the similarity measure only with the domain block from the same class. In the meanwhile, we consider the special property of the Dihedral transformation so that only four transformations are required to calculate the similarity. Therefore the encoding time can be further reduced. Experiments are conducted on 1 image using 6 methods including the full search method, discrete wavelet transform (DWT), PSO, SGA, ANN and the proposed method. Experimental results shows that the proposed method outperform all the other 5 methods. In average, the proposed method is about 181 times faster in comparison to the full search method with only 1.56 dB decay in image quality. Comparing to Wu's schema genetic algorithm (SGA) [2], the proposed method is better than the performance of

Manuscript received June 5, 2014
Manuscript revised June 20, 2014

SGA and ANN method[12]. Moreover, the encoding speed of the proposed method is faster than that of the full search method, better retrieved image quality.

2. FRACTAL IMAGE COMPRESSION

In local self-similarity property in a nature images. The fundamental idea is coming from the Partitioned Iterated Function System (PIFS). Suppose the original gray level image f is of size m × m. Let the range pool R be defined as the set of all non-overlapping blocks of size n × n of the image f, which makes up (m/n) 2 blocks. For obeying the Contractive Mapping Fixed-Point the domain block must exceed the range block in length. Let the domain pool D be defined as the set 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 pool R is composed of (256/8) × (256/8) = 1024 blocks of size 8 × 8 and the domain pool D is composed 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 constructed by searching all of the domain blocks in the D to find the most similar one and the parameters representing the fractal affine transformation will form the fractal compression code for v.

To execute the similarity measure between range block and domain block, In the size of the domain block must be first sub-sampled to 8 × 8 such that its size is the same as the range block v. Let u denote a sub-sampled domain block. The similarity of two image blocks u and v of size n × n is measured by mean square error (MSE) define

$$\mathrm{MSE}(u,v)=\frac{1}{n\times n}\sum_{j=0}^{n-1}\sum_{i=0}^{n-1}\left(u(i,j)-v(i,j)\right)^2. \quad (1)$$

The fractal transformation allows the eight Dihedral transformations in Table 1, Tk: k = 0, …, 7, of the domain blocks. If the coordinate origin is assumed to locate at the center of the block, the transformations T1 and T2 correspond to flip the block along horizontal and vertical line, respectively. T3 is the flip along both 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.

The fractal coder also allows the adjustment of the contrast scaling p and the brightness offset q on the block u. Thus the similarity is to minimize the quantity e = || p uk + q − v||, where uk = Tk(u), 0 ≤ k ≤ 7, are the 8 orientations of u. By direct computation, p and q can be computed by

$$p=\frac{n^2\langle u_k,v\rangle-\langle u_k,\vec{I}\rangle\langle v,\vec{I}\rangle}{n^2\langle u_k,u_k\rangle-\langle u_k,\vec{I}\rangle^2}$$

$$q=\frac{\langle v,\vec{I}\rangle-p\langle u_k,\vec{I}\rangle}{L^2}$$

where L2 is the number of pixels in the block of the range pool 8 × 8 vector with all entries being 1, and the Euclidean inner product of two vectors. Finally, the position (i, j) of the domain block (after sub-sampled, it is denoted by u), the contrast scaling p, the brightness offset q, and the orientation k constitute the fractal code of the given range block v. For each range block v, it will make up a fractal code of i, j, k, p and q.

Table 1.The 8 transformations in the Dihedral group

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

In the decoding process, In first make up the 1024 affine transformations from the compression codes. We choose one arbitrary image as the initial image and then perform the 1024 affine transformations on the image to obtain a new one. The transformation is proceeded recursively.

According to Contractive Mapping Fixed-Point sequence of image will converge. The stopping criterion of the recursion is designed according to user’s application and the converged image is the retrieved image of fractal coding.

3. FAST FRACTAL IMAGE ENCODING

3.1. Particle Swarm Optimization (PSO)

A population-based algorithm is PSO for searching global optimum. To simulate a simplified social behavior is the way of original idea of PSO[9]. Similar to the crossover operation of the GA, in PSO the particles are adjusted toward the best individual experience (PBEST) and the best social or global experience (GBEST). However, PSO is unlike a GA, why because in that each potential solution, particle is ‘‘flying” through hyperspace with a velocity, the particles and the swarm have memory for process; in the population of the GA memory does not exist.

Let xj,d(t) and vj,d(t) denote the dth dimensional value of the vector of position and velocity of jth particle in the swarm, respectively, at time t. The PSO model can be expressed as

$$v_{j,d}(t) = v_{j,d}(t-1) + c_1.\phi_1.(x^{*}_{j,d} - x_{j,d}(t-1)) + c_2.\phi_2.(x^{\#}_{d} - x_{j,d}(t-1)),$$

$$x_{j,d}(t) = x_{j,d}(t-1)\ v_{j,d}(t),$$

Where $x^{*}_{j,d}$ (PBEST) denotes the best position of jth particle up to time t-1 and $x^{\#}_{d}$ (GBEST) denotes the best position of the whole swarm up to time t-1, φ1 and φ2 are random numbers, and c1 and c2 represent the individuality and sociality coefficients, respectively. The steps involved here is the population size is first determined, and the

velocity and position of each particle are initialized. Each particle moves according to fitness is then calculated. Meanwhile, the best positions of each swarm and particles are recorded. Finally, as the stopping criterion is satisfied, the best position of the swarm is the final solution. The block diagram of PSO is displayed in and the main steps are given as follows:

- Initialize the PSO parameters.
- **For each particle (t_x, t_y), fetch the domain block at (t_x,t_y) in the image. Sub-sam-ple the block and denote it by *u*.**
- Obtain Dihedral transformed u_k, k = 0, □, 7. Calculate the contrast scaling p_k by minimizing the MSEs and brightness offset q_k by taking the median of the final residuals. The corresponding MSEs, which are treated as the cost of the given particle, are obtained during the process.
- **Update the *p*best and the *g*best if required. The corresponding fractal codes are also updated accordingly.**
- If stopping criterion is met, then stop.

Fig 1.(a) Original image of Lena

Fig 1.(b) Full Search.

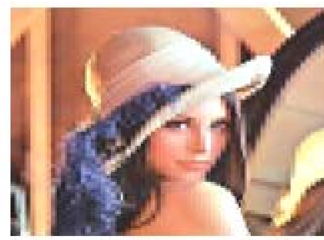

Fig 1. (c)Wavelet Classification.

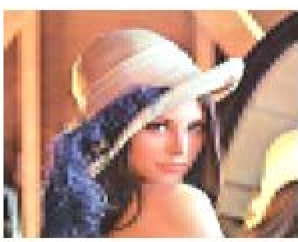

Fig 1.(d) ANN.

Fig 1.(e) SGA.

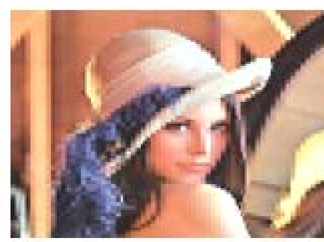

Fig 1.(f) PSO.

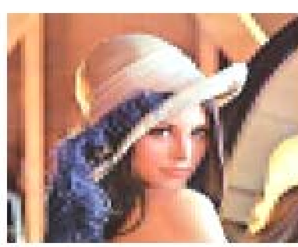

Fig 1.(g)) Proposed method.

3.2. Dihedral Transformation

To each range block, we must calculate the similarity measure with all eight transformed blocks of domain block according to the Dihedral transformations find the best match. The relations of F10 and F01 after applying Dihedral transformations, It is clear that all items are ± F10 or ± F01. This fact can be utilized to further reduce the encoding time. For example, the transformation T1 is to flip the block along the horizontal line. relations between the coefficients of the T1 transformed block to the original block f can be easily calculated as it separate the unit circle in the first quadrant into two regions Ω1 and Ω2 according to the line θ = 45°. For a given range block v, we pick a domain block u. If u and v are located in the same region, say Ω1, then we need only four Dihedral transformations, Tk: k = 0~3 performed on u because the transformations Tk: k = 4~7 will move u another region i.e., Ω2. The 4 transforms Tk: k = 0~3 or Tk: k = 4~7 have the same edge directions since their |F10| and |F01| are the same. Therefore, there are only four MSE computations required. On the other hand, if u and v are located in the different region, then we need only four Dihedral transformations, i.e., Tk: k = 4~7. From the argument above, the amount of MSE computations will be reduced two times.

4. PROPOSED METHOD

In the proposed fast fractal encoding using PSO, reduce the encoding time by reducing the searching time to find a best match domain block for the given range block from all domain blocks.

1 Set the swarm size and particle's parameters.

2 If the type of domain block is the same as that of range block, go to step 3, otherwise, go to step 5.

3 If u and v belong to the same region, only Tk: k = 0~3 are performed. Otherwise, only Tk: k = 4~7 are performed.

4 Calculate the MSE.

5 Update particle's position and velocity.

6. If the pre-specified number of iteration is reached, then stop.

7 Go back to step 2.

5. EXPERIMENTAL RESULTS

The results have been compared to the full search FIC mentioned in the previous sections in terms of encoding time and PSNR of fast fractal encoding using PSO.

The distortion or error between the original image f and the decoded image g caused by lossy compression process is measured in peak signal to noise ratio (PSNR) defined by

$$\mathrm{PSNR} = 10\log_{10}\left(\frac{255^2}{\mathrm{MSE}(f,g)}\right)$$

where MSE is defined (1) in The tested image on Lena in which each is a gray scale image of size 256 × 256 selected from the CVG-UGR image database[10] The related PSO parameters swarm size, number of clusters, and inertial weight, are set as 40, 4 and 0.9, respectively. The velocity in is limited in and the maximal number of iterations is set as 30.

Table 2. Simulation results for PSNR and comparison.

Image	*Lena*
Full search	26. 910
Wavelet Classification	26. 812
ANN	25.731
PSO	25. 643
SGA	25. 338
Proposed Method	9. 2150

Table 3. Simulation results for CPU time(s) and comparison.

Image	*Lena*
Full search	1433. 260
Wavelet Classification	482. 945
ANN	245.230
PSO	41. 267
SGA	14. 600
Proposed Method	8. 520

Table 4. Simulation results for MSE Computation and comparison.

Image	*Lena*
Full search	475,799,542
Wavelet Classification	158,664,808
ANN	111,657,607
PSO	10,166,262
SGA	2,835,477
Proposed Method	2,114,244

See Figure, 1 (a) show the original image for decoding, see Figures, 1(b)- (c) (d) (e) (f) (g) show retrieved images of Full Search, Wavelet Classification, ANN, PSO,SGA and proposed methods have PSNR 26.910 dB, 26.812 dB, 25.731
25.643 dB, 25.338 dB, 9.2150 dB respectively. Executing times, The results of the proposed method is listed in the tabular column. Compared to the Full search method, the speedup ratio is about three times faster. The detailed results of PSNR, executing time, and the amount of MSE computations and CPU time of the image listed in Tables (2-3-4) respectively. The retrieved image qualities are very close. The CPU time of the proposed method is 8.520 seconds, which is the least. The speedup

ratio with respect to the full search method shown in that is low. Under the condition of similar quality of decoded images, the encoding time of the proposed method reduces about 181 times which is better than that of the SGA method. As an complexity analysis, the amount of MSE computations in of the proposed method for lena image is 2,114,244 which is 225 times of the amount of the full search method, which is shown in the last column. As demonstrated, the proposed method has better performance that that of other methods.

6. CONCLUSION

In this paper, particle swarm optimization method is adopted with classification and Dihedral transformation in order to speedup the fractal image encoder. By using particle swarm optimization (PSO) based proposed method for fractal coding can reduce CPU time, PSNR, MSE Values and produces better compression ratio at acceptable quality, when comparing with existing full search, wavelet classification ANN, PSO and SGA methods.

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