Fractal Image Compression Coding Optimization based on Adjacent Pixels

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Abstract: Due to the need to search and match repeatedly in the same range block of image, the common optimization fractal image compression coding method has high computational complexity, which affects the image quality after compression coding. Aiming at the above problems, the fractal image compression coding method based on adjacent pixel optimization is studied. The image fractal code is constructed to simplify the steps of image fractal processing. The compression observation matrix is designed based on the principle of adjacent pixels, and the image compression coding is optimized by genetic algorithm under the constraint of the observation matrix. With image compression coding method based on fuzzy clustering optimization of contrast experiment, the experimental results show that the method of average encoding time is about 3/8 of the contrast method, encoded image compression ratio and peak signal to noise ratio are much higher than that of contrast method, namely the coding method based on adjacent pixels optimization performance is better, a higher application value.

Keywords: Adjacent pixels; Fractal image; Compression coding; Optimization method; Genetic algorithm

1. Introduction

At present, the problem of too much data has become a very difficult bottleneck in the development of multimedia technology and mobile communication. Data compression is an effective solution. Because of the strong correlation of source data, data compression is not only necessary but also possible. Fractal image compression coding is a new data compression method with great potential. Fractal image compression coding is a new image compression coding method based on iterative function system theory and patchwork theorem. It achieves the purpose of image compression by removing the redundancy of self-similarity between the whole and the parts of the image. It has attracted worldwide attention due to its high compression ratio, resolution independence, fast decoding and other superior features [1].

There are many directions to optimize the effect of fractal image compression coding, which can be summarized as: to establish a more effective matching block search space; A more efficient search method for matched blocks; Search for more convenient and accurate affine transformation applied to matching block; Search for a more reasonable segmentation method of image range block; A more effective representation and quantification method for fractal parameters. The method based on fuzzy clustering optimization mentioned in literature [2] uses fuzzy clustering algorithm to determine the final category number through its own objective function, and then optimizes the encoding and decoding speed of the image compression encoding method. Although this method has good image processing effect, in the process of image encoding and decoding, it is necessary to repeatedly search for matches in the same range blocks of images, which is of high computational complexity, and is not suitable for the compression and encoding processing of a large number of images [3]. Based on the above analysis, this paper studies the fractal image compression coding method based on adjacent pixel optimization. The following is the research content.

2. Research on Fractal Image Compression Coding Method based on Adjacent Pixel Optimization

2.1. Construct image fractal code

Constructing image fractal code can improve the efficiency of image compression coding. It is assumed that the gray level of the input image of the encoder is G and the size is $N \times N$. If the image block is $\{R_i\}_{0 \le i < m}$, the transformation of the image block with the size of $J \times J$ can be completed in the following two steps.

Step 1: Construct geometric transformation φ_i: select a size of $D \times D$ Domain block $\mu|D_i$, which can be compressed into a size of $J \times J$ image block $\varphi_i(\mu|D_i)$;

Step 2: Processing of the compressed Domain block $\varphi_i(\mu|D_i)$. Find an image transform f_i that minimizes the error between $f_i o\varphi_i(\mu|D_i)$ and $(\mu|R_i)$. By defining a Domain block pool Ω, it consists of all D_i blocks larger than R_i that can be obtained from the original image. In addition, an affine transformation pool Γ can be defined, which consists of all the discrete image blocks affine transformation f_i.The coding of image block $\mu|D_i$ is to find a best image block of $(D_i,R_i)\in\Omega\times\Gamma$, so as to minimize the error of $d(u|R_i, f_i o\varphi_i(\mu|D_i))$ [4].

The steps to directly search for an optimal match on (D_i,R_i) are as follows. An original Domain block pool Ω can be obtained by sliding a rectangular window of $D\times D$ ($D=2J$) over the original image. First of all, the upper-left coordinate of this window is at the point (0, 0). And then it moves from one position to another. To speed up coding, instead of moving pixel by pixel, you can move δ_h pixels horizontally to the right and δ_v vertically down, and the entire window is always completely in the image. Typically $\delta_h=\delta_v=J$ or $J/2$.

The image blocks in the Domain block pool can then be categorized. According to the research, it can be divided into shadow class, edge class and texture class. The shadow class is relatively smooth, the gray level change is not very serious image block. Edge class is the image gray level changes very much, usually the image edge [5]. Texture classes are classes that vary in grayscale moderately, usually with some texture, but not as much as edges. Typically, shaded classes are not used for Domain block pools. Because, a shadow class block in any image block transformation is still a shadow class; And the shadow class can be generated by the grayscale absorption transform. Moreover, under any non-gray absorption transformation, the Domain block keeps its classification unchanged. That is, under any non-grayscale absorption transformation, texture class is still texture class, edge class is still edge class. After the construction of image fractal code is completed, a compression observation matrix based on adjacent pixels is designed to reduce the difficulty of image compression coding.

2.2. Compression observation matrix design based on adjacent pixels

The local pixels in the image have a certain spatial correlation. The complexity of fractal image compression coding can be reduced by using the correlation between image pixels. In order to ensure the information of the whole image block to be compressed, the target point is uniformly selected on the whole image block according to the sampling rate. According to the image sampling rate SR, the following three steps are used to select the target point.

Step 1: Divide the ring area with the 2×2 area in the center of the image block as the initial area, as shown in the figure below, and form a square ring area one pixel outward at a time. If the image block size is 16×16, there are 8 concentric ring regions (including the initial region); If the image block size is 32×32, there are 16 ring regions [6].

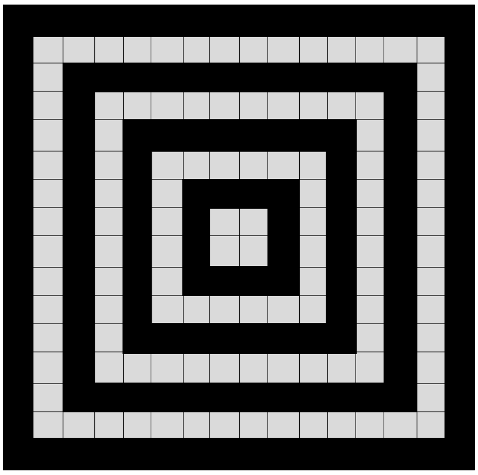

Figure 1. Division of the annular region of the image

Step 2: Calculate the number of target points in each ring region. According to the total number of pixel points and sampling rate in each ring region, the number M_i of target points in each region is calculated.

$$M_i = round(SR * N_i) \quad (1)$$

In formula (1), N_i is the total number of pixels in the i th ring region.

Step 3: Ring selection of the target point. In order to evenly distribute the target points in the image block, the annular region was divided into four directional intervals (N, S, E, W). According to the target points determined in step 2, the target points were cycled in order of $N\to S\to E\to W$, and the target points were symmetrically taken [7]. As shown in the following figure, the selection starts from the first point in the direction of N, then the last point in the direction of S, the first point in the direction of E, and finally the last point in the direction of W. If there are multiple target points in one direction, the next point is taken according to the number of target points calculated in equation (1) and the number of total pixels in the ring region at equal intervals. If a complete loop is not completed at the end of the current ring region, the loop continues to the next ring region until all the target points are filled.

After the target point is determined, a binary sparse matrix P with dimension of $M\times B^2$ (where M is the number of observed values at the sampling rate) can be easily generated, in which only one element in each row is 1, corresponding to the corresponding target point in the image block during compression processing. Due to natural images have a certain correlation between adjacent points, considering the characteristics of the adjacent pixel values are similar but not identical, using Gaussian probability density function of target point weights were scattered, the part weight spread to the adjacent pixels, so that each value of the compressed domain not only contains the target information, also contain adjacent pixels of a small amount of information, can further improve the quality of reconstruction. The Gaussian probability density function is used to disperse the weights in the obtained binary sparse matrix in both horizontal and vertical directions [8]:

$$w_k = Ae^{-\frac{(x_i-x_{tar})^2}{2\sigma_x^2}}e^{-\frac{(y_i-y_{tar})^2}{2\sigma_y^2}} \tag{2}$$

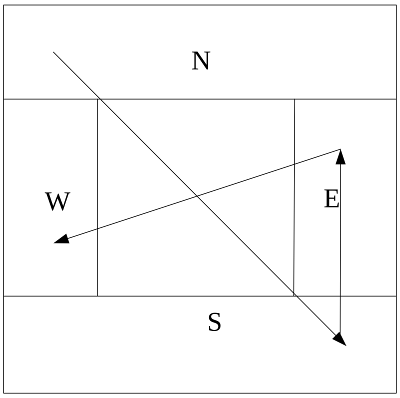

Figure 2. Schematic diagram of target point acquisition in loop

In formula (2), w_k represents the element value distribution in row k of the matrix; (x_{tar}, y_{tar}) represents the target point coordinates corresponding to the element in the matrix; (x_i, y_i) represents the coordinates of all the pixels in the image block of size $B \times B$; A is amplitude; σ_x is the variance in the direction; σ_y is the variance in the y direction, and the selection of each parameter value is related to the sampling rate during image collection. After the compression observation matrix based on adjacent pixels is designed, the image compression coding is optimized using the simulated genetic algorithm.

2.3. Achieve compression code optimization

In this paper, simulated genetic algorithm is used to optimize the image compression coding. The genetic algorithm mainly draws on the characteristics of biological evolution, and obtains the optimal solution by coding the optimization problem, constructing and applying the adaptation function, and crossing variation.
The image compression coding method optimized by genetic algorithm is shown in the following figure:

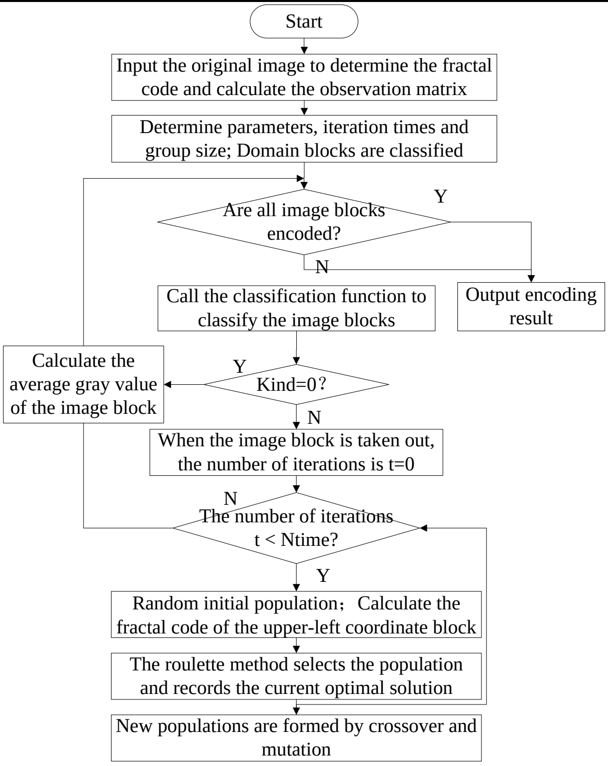

Figure 3. Image compression coding optimized by genetic algorithm

Under the processing of observation matrix, the upper left coordinate of the fractal image is selected for binary coding. According to the fitness function of the following formula, the fitness function values of each individual in the initial population were calculated [9].

$$F_i = fitness\left[pop_i(t)\right] \tag{3}$$

In formula (3), $pop_i(t)$ is the i th individual in the population. After the fitness function value of all individuals in the population, judge whether the genetic algorithm stop rule is satisfied. If the stop rule is satisfied, the algorithm stops. Otherwise, calculate the probability according to the following formula:

$$p_t = 1 - \frac{F_i}{\sum_{j=1}^{groupN} F_j}, i = 1, 2, \cdots, groupN \tag{4}$$

In formula (4), p_t is the probability of similarity between individual i and individual j. According to the above probability distribution, some individuals were randomly selected from $pop(t)$ to form a population by roulette [10]:

$$newpop(t+1) = \left\{pop_j(t) \middle| j = 1, 2, \cdots, groupN\right\} \tag{5}$$

In formula (5), $newpop(t+1)$ is the new population formed. Through genetic crossover, a population containing N individuals is obtained. With a small probability, individuals will be mutated, $t = t + 1$, and a new population will be obtained. The fitness function value of individuals in the population will be calculated again. Repeat the above process until the optimal solution is obtained, that is, the optimal compression coding result of the image is completed. So far, the fractal image compression coding method based on adjacent pixel optimization has been studied.

3. Experiment

In this paper, a fractal image compression coding method based on adjacent pixel optimization is proposed. In order to test the effectiveness of this method, an experiment is carried out below.

3.1. Experiment content

This experiment is a comparison experiment, in which the fractal image compression and coding method based on the optimization of fuzzy clustering algorithm is adopted as the comparison method, and the fractal image compression and coding method based on the optimization of adjacent pixels is proposed in this paper as the verification method. The experiment is a simulation experiment. The experimental platform is equipped with Windows 10 operating system and Intel core i7 CPU with 2.35ghz processor. The algorithm operation and data processing software is MATLAB 2016. Test images were used: couple, Lena, woman2, crowd, etc. The comparison index of the experiment is the compression ratio and peak signal to noise ratio (PSNR) when two optimized image compression coding methods are used to process the experimental image. By comparing the above two indexes, the performance of the two optimized compression coding methods is measured.

3.2. Experimental data

The test atlas parameters used in the experiment are shown in the following table.

Table 1. Parameters of experimental test image set

Atlas	Size	Grey value	K-value
Couple	216×512	234	1～5
Lena	512×512	255	10～20
Woman2	216×216	228	20～30
Crowd	512×512	255	40～50

The comparison group method and the verification group method respectively compress and encode the test atlas with parameters as shown in the table above, and record the compression ratio and peak signal-to-noise ratio data of the atlas after processing by the two methods. Analyze the recorded data and draw experimental conclusions.

3.3. Experimental results

The experimental results are shown in the following table. The data in the table are analyzed to draw relevant conclusions for this experiment verification.

Table 2 Comparison results were processed by the two methods

Atlas	K- value	Comparison method			Method in this paper		
		Encoding time /s	Compression ratio	PSNR/dB	Encoding time /s	Compression ratio	PSNR/dB
Couple	1	54.3	4.13	32.25	18.6	4.85	36.29
	3	55.6	4.12	33.42	19.5	4.62	37.09
	5	58.2	4.13	34.81	20.6	6.92	37.92
Lena	10	60.5	5.36	34.88	21.3	11.98	38.3
	15	62.5	6.61	35.16	22.6	14.27	38.52
	20	63.1	8.96	35.32	23.2	18.79	38.64
Woman2	20	64.9	11.27	35.49	23.2	20.71	38.8
	30	65.4	13.84	35.56	23.4	22.85	38.86
Crowd	40	65.3	15.59	35.66	24.6	25.34	38.89
	50	65.6	17.91	36.17	24.5	27.06	39.24

Analysis above, the two methods for different K-value the same atlas compression processing, contrast method of compression ratio is smaller than the method of dealing with the image compression ratio, with the increase of K-value, two methods of image compression ratio increased to different extent, but the method of processing the image compression ratio increasing degree is bigger. After processing the test atlas by different methods, the PSNR value of the image processed by the method in this paper is much higher than that of the image processed by the comparison method. It shows that the image quality after the method in this paper is better. The average coding time of the two methods in this test was calculated, and the comparison method was 64.54s, while in this paper it was 22.15s. The average coding time of the method in this paper was about 3/8 of the average coding time of the comparison method. It shows that the method studied in this paper is more efficient to compress and encode images.

To sum up, the fractal image compression and coding method based on adjacent pixel optimization studied in this paper has higher quality and efficiency in image processing, and higher practical application value.

4. Conclusion

Image compression coding is one of the most widely used methods in the field of image processing. In this paper, a fractal image compression coding method based on adjacent pixel optimization is proposed to solve the defects of the conventional fractal image compression coding methods. Through the comparison experiment with the compression coding method based on fuzzy clustering algorithm, it is proved that the application effect of the proposed method is better.

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