Research on Fractal Image Coding Method Based on SNAM Segmentation Scheme

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Abstract. Adaptability of the partition method of fractal image compression to gray level textures directly influences the total number of partition blocks and image decoding effects. Hence, it is of critical significance to find a partition method which can accurately reflect image gray level distribution and visual threshold linkage relations in order to speed up encoding and enhance decoding quality. Therefore, in this paper, the SNAM (Square of Non-symmetry and Anti-packing Model) partition method is optimized by thresholds. The optimized method is employed to improve fractal encoding. On the basis of the organic relations between local image textures, human vision threads and encoding efficiency as well as decoding quality, a self-adaption sub-blocks partition method based on a square non-symmetry, anti-packing model and human vision system is proposed. With such method, partitioned image sub-blocks can accurately reflect gray level distribution of images, while the number of partitioned image sub-blocks is reduced. In this way, the calculation and matching times are reduced in encoding. Encoding time is reduced in addition to improvement of restored image quality. Compared with the basic fractal encoding method, the speed is increased by over 30 times.

Keywords: Fractal image coding · SNAM segmentation · Threshold optimization · Human visual system

1 Introduction

Fractal image coding technology was first proposed by Barnsley [1]. It is mainly employed in research fields due to its complex operations. Fractal image compression coding technology can be studied and applied by researchers due to proposition of the image coding algorithm based on fractal block search [2]. The basic fractal image coding algorithm is proposed based on the fractal block algorithm. An image is divided into non-overlapping R blocks and overlapping D blocks. Each block has a certain fractal structure. Using the similarity between image blocks and combined with the iterative function system theory and collage theorem, the D block that is most similar to each R block is found, and relevant parameters are recorded to complete the fractal image coding process.

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The basic fractal image coding algorithm has the outstanding characteristics such as ultra-high compression ratio, simple restoration and good restoration effect while it is also disadvantaged in long coding time and complex coding process. In response to the above-mentioned problems, researchers at home and abroad have made considerable efforts [3–6]. They mainly carry out research from the perspectives of image segmentation, combination of transform domain, codebook reduction, matching method and decoding method. The research aims to lower the impact of long fractal coding time on coding efficiency and ensure the quality of reconstructed images. The fractal image coding method based on transform domains processes the image before fractal coding, and adopts fractal coding to the processed image. Both the hybrid coding method combining fractal and wavelet transform proposed in Literatures [7–9] and that integrating fractal and DCT (Discrete Cosine Transform) proposed in Literature [10] have achieved good image restoration results. Literature [11] proposes a search strategy based on iterative control. With this strategy, the search process is controlled through the iterative update times of fractal codes, and the search termination time is set. Besides, the inefficient and invalid searches in the search process are removed, and the coding speed is greatly improved. Literature [12] classified D blocks by fuzzy clustering according to the complex exponential moment invariants of D blocks, further finding the best matching D blocks according to the complex exponential moment invariants of R blocks, thus improving the coding speed while maintaining better decoded image quality. Literature [13, 14] propose a rapid fractal image coding algorithm based on square weighted centroid features, which converts global search into local search and limits the search range in order to reduce the number of codebook.

The paper starts with the block segmentation method, and uses the adaptability of asymmetric segmentation to image gray vein to affect the total amount of blocks and decoding effect. SNAM (Square of Non-symmetry and Anti-packing Model) [15] can segment adaptive image veins through asymmetric inverse layout. The total amount of image blocks and the number of basic representation units generated are smaller than those of extensively used representation methods such as quad tree. Therefore, the paper considers optimizing SNAM segmentation by threshold and applying it to improve fractal coding, aiming to provide a new research idea and find out the accurate linkage relationship among image gray distribution, visual threshold, coding speed and decoding quality.

2 Fractal Coding Algorithm Based on SNAM Segmentation Scheme

2.1 Basic Fractal Coding Algorithm

In fractal coding, an image is first divided into $n \times n$ non-overlapping range blocks (R blocks for short) and domain blocks (D blocks for short) with an allowable overlapping size of $2n \times 2n$. Then, each D block is contracted into $n \times n$ sub-blocks by averaging 4-neighborhood pixel values so as to match the size of R blocks. Meanwhile, all the contracted D blocks undergo 8 equidistant transformations to form a codebook Ω.

In the coding stage, for each R block, the best matching D block and self-affine transformation ω are found in the codebook Ω by the global search method. Therefore, the mean square error of ω(D) and R is minimized. In order to find the best matching block of R block, the following minimization problem needs to be solved.

$$\|R - (\mathrm{s} \cdot D_m + \mathrm{o} \cdot \mathrm{I})\| = \min_j \left\{ \min_{s,o \in R, |s|<1} \left\| R_i - \left(s \cdot D_j + o \cdot I \right) \right\| \right\} \tag{1}$$

where: m represents the best matching block sequence number of the R block, $I \in R^{n \times n}$ is a constant block with all elements being 1, and R = $(r_1, \cdots, r_k, \cdots, r_N)$ and D = $(d_1, \cdots, d_k, \cdots, d_N)$ (N = n × n) respectively represent vectors obtained after the pixel gray values of the R block and the D block are vectored in a way.

The solution of Eq. (1) is extremely difficult. Hence, in order to reduce the computational complexity, the constraints $|s| < 1$ in Eq. (1) are ignored first, and the minimization of the inner constraints of Eq. (1) is transformed into the minimum problem of Eq. (2) for solution. Then, the contrast factor that does not meet the constraints is truncated for compensation.

$$\mathrm{E(R, D)} = \min_{s,o \epsilon R} \|R - (s \cdot D + o \cdot I)\| \tag{2}$$

Then the outer layer minimization problem of Eq. (1) is solved:

$$\mathrm{E(R, D)} = \min_{D \epsilon \Omega} E(R, D) \tag{3}$$

Finally, after the solution of formula (1) is transformed into suboptimal solutions (2) and (3), the R-block fractal code obtained is a quaternary (m, $\widehat{s_i}$, $\widehat{o_i}$, t), wherein $\widehat{s_i}$, $\widehat{o_i}$ is the quantized value of s_i, o_i, and t denotes the isometric transformation sequence number. The fractal code of the original image is composed of fractal codes of all R blocks, describing a compression transformation that makes the image approximately invariant. Decoding is generated by iterating the compression transform described by fractal codes on any initial image.

2.2 Gray Image Representation of SNAM

The new image representation method should be able to effectively save storage space and have an efficient operation mode, which is suitable for various processing processes such as image compression, feature extraction and restoration. At present, the more mature quad-tree image representation method has achieved good results of application to the segmentation method in image compression. For example, Literature [16] uses the quad-tree segmentation method combined with the characteristics of human visual system to improve the fractal coding method, which can speed up the coding speed besides controlling the decoding distortion within the range imperceptible to human eyes. Literature [17] proposes a rapid fractal image coding algorithm based on HV segmentation to improve image adaptive performance and accelerate fractal code extraction. The above studies show that the adaptability of fractal coding segmentation method to gray vein is directly associated with the total number of blocks and decoding effect. At the same time, the application of appropriate image representation methods to fractal coding can effectively improve the speed of fractal coding. The SNAM representation method proposed in Literature [15] adapts image vein through asymmetric inverse layout segmentation. The total amount of data and the number of basic representation units generated are less than those of widely used representation methods such as quaternary tree. Therefore, the present study applies SNAM representation method to the segmentation scheme of fractal coding, which can effectively shorten the coding time of fractal image compression.

The framework of square sub-patterns is defined in advance. For a given pattern that has been laid out, the pattern is transformed into a combination of a series of square sub-patterns with different scales based on the inverse layout algorithm. The abstract description of SNAM representation in this paper is presented as follows:

If the original mode is Γ and the reconstructed undistorted mode is Γ', SNAM will be undistorted mapping from Γ to Γ':

$$\Gamma' = \mathrm{W}(\Gamma) \tag{4}$$

where: W () is a forward mapping function, that is, a coding function.

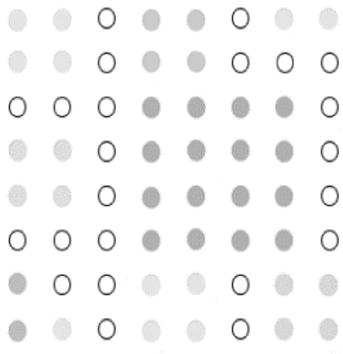
The forward encoding process is

$$\Gamma' = \bigcup_{j=1}^{n} p_{s_j}(v, A|A = \{a_1, a_2, ..., a_m\}) \tag{5}$$

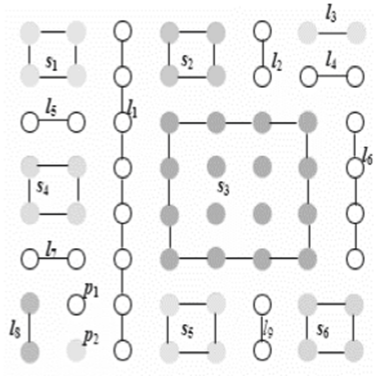
where Γ' represents the synthesized mode after inverse layout coding; a square sub-pattern set $P = \{Ps\}$ is predefined, n is the total number of square sub-patterns contained in the Γ, and Ps_j is the j-th square sub-pattern in Γ; V is the value of Ps_j, A is the parameter set of square sub-patterns; a_i $(1 \le i \le m)$ denotes the i-th shape parameter of the square sub-pattern, and m is the total number of parameters of the square sub-pattern.

Figure 1 shows the results of inverse layout encoding and storage of a gray image by employing SNAM method. Figure 1(a) shows the original gray image G of a given size of $2^n \times 2^n$ $(n = 3)$. Figure 1(b) is a result of SNAM inverse layout with the application of raster scanning. Six square sub-patterns $(s_1, s_2, s_3, s_4, s_5, s_6)$, nine line segments $(l_1, l_2, l_3, l_4, l_5, l_6, l_7, l_8, l_9)$ and two isolated points (p_1, p_2) are extracted from the original image. Figure 1(c) is the image matrix of G. Figure 1(d) shows results of representing T using the above sub-pattern.

By combining SNAM image representation (a predefined image laid out), and using the inverse layout algorithm (essentially a flexible asymmetric segmentation method aimed to find the sub-pattern in the largest area within the threshold range), square sub-patterns with different scales are extracted from an image, which is represented by their combinations. It is applied in the classification coding algorithm to segment the image into sub-blocks. During the segmentation, in view of the characteristics of HVS (Human Visual System), a threshold is set, the image is divided into blocks, and the gray value in the block is within a given threshold range, namely, the similarity of the image blocks in the rectangle will be the furthest. Therefore, it can realize the differential processing of different detail parts of the image, and effectively keep the vein features of the image, namely, the flat part in the image is segmented by relatively large image blocks, thus improving the compression ratio. Regarding the detailed part in the image, relatively small image blocks are used for segmentation, thus ensuring higher reconstructed image



(a) Results of the gray image G with size of 8 × 8 and 8 gray scales



(b) Results of SNAMG inverse layout of G

y/x	000	001	010	011	100	101	110	111
000	100	100	111	010	010	111	101	101
001	100	100	111	010	010	111	111	111
010	111	111	111	000	000	000	000	111
011	100	100	111	000	000	000	000	111
100	100	100	111	000	000	000	000	111
101	111	111	111	000	000	000	000	111
110	001	111	111	101	101	111	011	011
111	001	101	111	101	101	111	011	011

(c) Image matrix of G

s_1={(000,000),010,100},s_2={(011,000),010,010}
s_3={(011,010),100,000},s_4={(000,011),010,100}
s_5={(011,110),010,101},s_6={(110,110),010,011}
l_1={(010,000),(010,111),111},l_2={(101,000),(101,001),111}
l_3={(110,000),(111,000),101},l_4={(110,001),(111,001),111}
l_5={(000,010),(001,010),111},l_6={(111,010),(111,101),111}
l_7={(000,101),(001,101),111},l_8={(000,110),(000,111),001}
l_9={(101,110),(101,111),111}
p_1={(001,110),111 },p_2={(001,111),101}

(d) Storage results of G

Fig. 1. Result of inverse layout segmentation and storage of a gray scale image

quality. The SNAM image representation method is applied to image segmentation, and the number of segmented blocks is much fewer than that of classical algorithm. In addition, the vein features of images can be well preserved.

2.3 Fractal Coding Algorithm Based on SNAM Segmentation Scheme

The basic principle of SNAM-based segmentation scheme is to use a segmentation threshold with the starting point gray value of each square as the matching reference value. As long as the gray value of each pixel is within the range of starting point gray value $\pm$ segmentation threshold, it can be considered as a gray square. This threshold is based on HVS characteristics. The segmentation threshold is set to distinguish different detail parts of the image. As a result, relatively good vein features of the image can be kept and the similarity of image blocks is likely to fall within the rectangle. In this way, sub-blocks of maximum size can be obtained, which thereby reduces the total number of blocks, and help achieve the purpose of shortening the coding time. On the premise of guaranteeing better decoding quality than that of the basic fractal algorithm, the method can speed up by approximately 30 times.

One typical feature of Human Vision System (HVS) refers to the nonuniform and nonlinear cognitive image. In other words, human eyes cannot completely recognize all the details and changes in images. The subjective sensing intensity of humans is associated with changes in the stimulus intensity. As shown in Fechner's law, with increasing stimulus intensity in geometrical progression, the sensing intensity caused thereby only increases by arithmetical progression, namely a logarithmic relation. Such sense can be vividly expressed by a visual threshold which means the value of a stimulus (interference or distortion) which can just be felt. Edges with varying brightness will "conceal" the signal feelings of nearby pixels, thereby reducing the visual sensitivity of human eyes, which is called the "concealment effect". Due to such feature of vision, human eyes can tolerate great quantization errors in edge areas of images. Therefore, influential factors on visual thresholds are contrast sensitivity and a concealment effect of a brightness threshold at a pixel point. In view of the uniqueness of HVS, human eyes' resolution ratios to gray levels are briefly tested to observe the changing scope of threads, within which image changes cannot be sensed. On this basis, the best threshold scope of the algorithm can be then predicted. The sensitive scope of human eyes to gray levels is generally within dozens of gray levels, wherein the gray level value is selected from 20–40. The SNAM partition solution is employed to test 5 images. Testing data is shown in Fig. 2, In order to ensure decoded image quality and encoding time, the encoding time and PSNR value are optimal when the thresholds of the 5 images are about 30. Therefore, the optimum threshold scope is set around 30.

SNAM segmentation scheme is the key to realize the algorithm in this paper. It is mainly used to adapt the image vein to divide the range blocks. The following displays a schematic diagram 3 of the fixed block segmentation method and SNAM segmentation method:

Fixed block segmentation is the segmentation method of the basic fractal image coding scheme, which is disadvantaged in that the gray vein features between the pixel values of the image are not considered. As shown in Fig. 3(a), even if there is little difference between the adjacent pixel values, they will be divided according to the

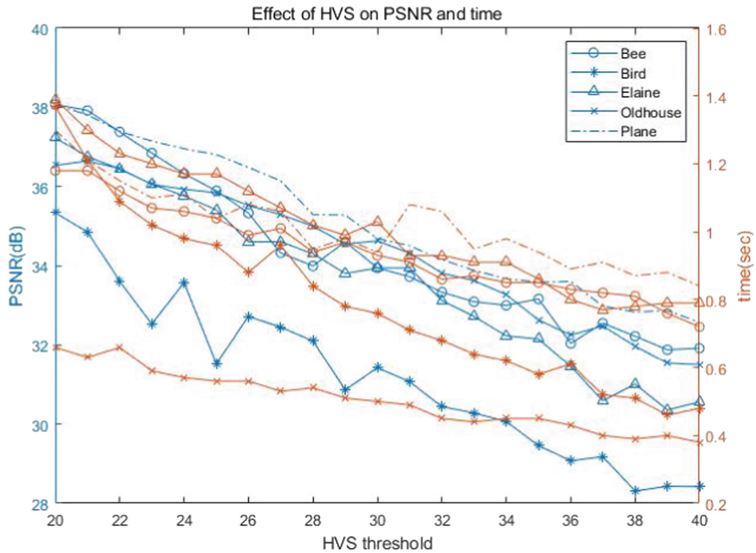


Fig. 2. Test effects of different thresholds

y/x	1	2	3	4	5	6	7	8
1	119	104	130	124	124	162	141	87
2	126	104	120	107	101	155	149	64
3	103	97	95	112	117	33	38	156
4	125	100	120	89	106	46	54	161
5	137	115	130	97	136	52	155	180
6	151	140	132	77	113	117	145	139
7	112	142	135	75	145	126	132	102
8	98	163	128	101	137	203	157	159

(a) 8 × 8 fixed block segmentation representation results

y/x	1	2	3	4	5	6	7	8
1	119	104	130	124	124	162	141	87
2	126	104	120	107	101	155	149	64
3	103	97	95	112	117	33	38	156
4	125	100	120	89	106	46	54	161
5	137	115	130	97	136	52	155	180
6	151	140	132	77	113	117	145	139
7	122	142	135	75	145	126	132	102
8	178	163	128	101	137	203	157	159

(b) 8 × 8 SNAM segmentation method representation results (threshold value is 30)

Fig. 3. Schematic diagram of block segmentation method and SNAM segmentation method

size. Different detail parts of the image cannot be treated differently, which can easily cause poor quality of the restored image. The key point of SNAM segmentation scheme refers to the segmentation threshold. The segmentation threshold is determined by the basis of human visual system (HVS). Therefore, the gray vein features between pixel values of the image are fully considered. The advantages of SNAM segmentation method can be observed from the above Fig. 3(b). Besides being able to better adapt to the vein features of the image, it can also effectively reduce the number of segmentation blocks, which can help subsequent algorithms decrease the amount of computation during matching calculation and thus effectively shorten the coding time. Although the SNAM segmentation method not only has a square sub-mode, but also has the line sub-mode and isolated point sub-mode, combining the advantages of all the aspects, this segmentation method can still improve the coding speed and decoded image quality of the algorithm on the premise of keeping the same compression ratio.

The specific steps of the coding algorithm:

Step 1. Set counting variables *square_num*, *l_num* and *p_num*, record the number of square sub-modes, the number of line segments and the number of isolated points generated in the inverse layout process, and assign an initial value of 0.
Step 2. Use the inverse layout algorithm based on SNAM as the basic idea, and aim at forming a square with the largest area. Set a threshold w, if the gray value of the pixel points is at $(z \pm w)$, continue to reverse the layout to form the square, and mark the pixel points involved in the square in G.
Step 3. Make $square\_num = square\_num + 1$, record the left upper vertex coordinates (x, y) of the square sub-mode, and perform dimension reduction transformation, namely $sp\_x, sp\_y \leftarrow K(x, y)$, to obtain one-dimensional (K code) coordinates sp_x, sp_y; record the side length and the gray value z, and then store sp_x, sp_y, length and z in the queue square, that is, square $square\{square\_num\} \leftarrow \{sp\_x, sp\_y, length, z\}$. Count and store line segments and isolated points in this way. Regarding line segments, store coordinates and pixel values of starting points and ending points as well as isolated points store point coordinates and pixel values.
Step 4. Repeat Step 2 to Step 3 and stop when there is no new sub-mode. Some square image sub-blocks with different sizes that do not overlap each other are obtained, which are called range blocks (R).
Step 5. Subsample the whole G once, wherein the size of the subsampled image G' *is* $(M/2) \times (M/2)$.
Step 6. Based on the total number of segmented R blocks *square_num*, transform it from 1 to *square_num*, wherein each count corresponds to an R block, and the square information stored in it is used to determine the sp_x, sp_y, length corresponding to the R block, and find out a best matching sub-block D with the same size as the R block in the sub-sampled image G'. Ensure that the square error between D' and R obtained after gray affine transformation and equidistant transformation of D is minimum, and just store line segments and isolated points.

For each range block R, record the following 5 parameters:

(1) The coordinates $(domain\_x, domain\_y)$ of the upper left corner of the best matching sub-block D searched.
(2) The sequence number t of the isometric transformation that makes R and D become the best match.
(3) Gray contrast factor s and gray translation factor p.

Specific steps of decoding algorithm:

Step 1. Assign any initial value to the size of $M \times M$.
Step 2. Set a counting variable *square_num* to correspond to the number of square sub-patterns generated in the inverse layout process, and assign an initial value of 0.
Step 3. Read fractal codes *{domain_x, domain_y, t, s, p}* according to fractal coding file, count by coding queue square *{square_num} {sp_x, sp_y, length, z}*, namely *square_num* = *square_num* + *1*, obtain one-dimensional (K-code) coordinates *sp_x, sp_y* and side length of the upper left vertex of each square sub-mode in sequence, apply collage formula to carry out operation, and make all R blocks form an iterative image.
Step 4. Output the reconstructed image *bumper* after 9 iterations.

In terms of isolated point sub-mode, only the coordinate point position and pixel value are stored during coding, while for line segment sub-mode, the coordinate value and average pixel value of the first and last pixels of line segment need to be stored. In decoding, only the corresponding positions of point mode and line segment sub-mode need to be filled.

3 Experimental Analysis

In order to verify the feasibility and efficiency of fractal image compression coding algorithm based on threshold optimization segmentation scheme, the author conducts an experimental comparison between this algorithm and the basic fractal compression algorithm. To ensure the unity of evaluation criteria, the basic fractal compression algorithm and the algorithm proposed in the present study adopt 1/2 subsampling method during matching D blocks. The experimental environment configuration includes, processor Intel(R)Core(TM)i7 9700, operating system Microsoft Windows 10 and development software Matlab 2021a. The experimental test images are shown in Fig. 4, involving figures, animals, scenery and other fields. The pictures are different in complexity, with strong representativeness and universality.

(a)bee (b) Elaine (c) old house (d) plane (e) bird

Fig. 4. Five 256×256 gray scale images used in the experiment

To make the algorithm proposed by paper comparable with the basic fractal coding algorithm, the proposed algorithm is improved on the basis of Jacquin's basic fractal algorithm. In Jacquin's basic fractal coding algorithm, the size of R block is 4×4, the size of D block is 8×8, and the step size of the sliding window of D pool is 8. Therefore, the number of range blocks after fixed block segmentation is: (256/4) × (256/4) = 4096. In the algorithm proposed by the paper, SNAM segmentation is optimized by threshold, and the size of range block is determined by the set threshold. There are usually many sizes. Because the complexity of each image is different, and the algorithm in the current work is based on the square asymmetric inverse layout model and the adaptive sub-block segmentation of the human visual system. The selection of the threshold Q affects the number of blocks in the range, the peak signal-to-noise ratio PSNR (unit dB), the coding time T (unit of s), and the compression ratio of C. Therefore, different images may have different thresholds to achieve the best segmentation effect. Meanwhile, the final determination of the best threshold needs to be tested many times.

With 256 × 256 × 8 standard gray images bee, elainel, old house, plane and bird as test objects, after performing many tests, this experiment obtains the segmentation data of the algorithm in the case that Q is the best threshold, as shown in Table 1. The fixed block segmentation data of Jacquin's basic fractal algorithm are shown in Table 2.

Table 1. Total number of range blocks under best threshold

Image	Bee	Elaine	Old house	Plane	Bird
Optimal threshold	29	30	30	38	29
Number of range blocks	3489	3634	2436	2908	3894
Line segment	17	11	63	77	12
Point	2962	2821	2601	4361	2702

Table 2. Number of Jacquin fixed block segmentation range blocks

Image	Bee	Elaine	Old house	Plane	Bird
Number of range blocks	4096	4096	4096	4096	4096

The algorithm in this paper improves the original SNAM gray segmentation method and optimizes SNAM segmentation by threshold. Therefore, under the optimal threshold Q segmentation, the number of range blocks segmented in this paper is compared with the total number of range blocks obtained by employing Jacquin's basic fractal algorithm, and the number of range blocks segmented in this paper is reduced. Through conducting the experiments, the coding time of the two methods is obtained, and the acceleration ratio is calculated, as illustrated in Table 3. At the same time, the PSNR values of the restored images by using the two methods are compared, as shown in Table 4.

As displayed in the data in Table 1, Table 2, Table 3 and Table 4, the old house picture has the highest speedup ratio and the highest PSNR restored, that is, the best quality. The reason refers to that the gray distribution of the image is relatively uniform. Therefore, after the optimal threshold Q segmentation, different details of the image will be differentiated. It can retain the vein features of a relatively good image, that is, the sub-blocks divided into uniform vein parts in the image are relatively large, thus

Table 3. Encoding time (s) and speedup ratio (%) using two methods

Image	Bee	Elaine	Old house	Plane	Bird
Jacquin's basic fractal algorithm	27.85	27.93	27.75	27.67	32.77
Algorithm proposed by the paper	0.93	1.03	0.5	0.94	0.76
Acceleration ratio	29.94	27.11	55.5	29.43	43.11

Table 4. PSNR (dB) values of restored images using two methods

Image	Vein	Elaine	Old house	Plane	Bird
Jacquin's basic fractal algorithm	30.99	28.79	27.51	24.15	28.89
Algorithm proposed by the paper	33.94	33.93	35.63	34.69	31.42

minimizing the number of range blocks. As a result, the coding time is less than other images in matching calculation, and the acceleration ratio is naturally the highest. The reason for the best quality of the image is not only that the gray distribution is relatively uniform, but also that the details are relatively simple. The details in the image can be processed better after setting threshold segmentation. In other words, the divided blocks will be relatively small. Thus, the transition between blocks is very good, and PSNR will be improved after the details of the restored image are processed. In a similar way, due to the complex gray distribution and many details of bird, the image has the lower acceleration ratio and the worst restored image quality.

Figure 5 shows the original images of bee, elaine, old house, plane and bird and the images reconstructed by two algorithms respectively. The reconstructed images of bee, elainel, old house, plane and bird using Jacquin's basic fractal algorithm are presented in Fig. 5(b), (e), (h), (k) and (m), respectively. Figure 5(c), (f), (i), (l) and (o) are the decoded images of bee, elainel, old house, plane and bird reconstructed by the algorithm in this paper when the optimal threshold Q is used. The PSNR value at this time is 33.94, 33.93, 35.63, 34.69 and 31.42, respectively. At this time, we can't find the difference between it and the original image subjectively. Objectively, the decoded PSNR also exceeds 30. Figure 5(k) shows a decoded image after plane reconstruction obtained by Jacquin's basic fractal algorithm. At this time, the PSNR is 24.15. At this moment, we can still observe the difference between it and the original image subjectively. The decoded PSNR does not reach 30, while the PSNR value of the image restored by this algorithm is 34.69, which is higher than Jacquin's basic fractal algorithm. Hence, the difference with the original image is basically invisible to naked eyes.

It can be easily found from Tables 3 and 4 that when the optimal threshold Q is used, the decoded image quality of the algorithm in this paper is better than that of the basic algorithm. The coding speed of the algorithm in this paper is about 30 times that of the basic algorithm, demonstrating that it is an effective image compression method.



(a) Original Bee image

(b) Bee image reconstructed by the basic algorithm

(c) Bee image reconstructed by the algorithm proposed in the paper



(d) Original elaine image

(e) Elaine image reconstructed by the basic algorithm

(f) Elaine image reconstructed by the algorithm proposed in the paper



(g) Original old house image

(h) Old house image reconstructed by the basic algorithm

(i) Old house reconstructed by the algorithm proposed in the paper

Fig. 5. Original image and image reconstructed by two algorithms

(j) Original plane image

(k) Plane image reconstructed by THE basic algorithm

(l) Plane image reconstructed by the algorithm proposed in the paper

(m) Original bird image

(n) Bird image reconstructed by basic algorithm

(o) Bird image reconstructed by the algorithm proposed in the paper

Fig. 5. continued

4 Conclusions

To conclude, a good block segmentation scheme can not only accelerate the fractal coding speed, but can also improve the restored image quality. Therefore, this paper proposes a threshold optimization SNAM segmentation scheme to improve fractal coding. In addition, the effectiveness of the proposed algorithm is confirmed by theoretical analysis and experimental simulation. However, there still remains room for improvement. For example, the isolated points and line segments in the image region that cannot form the SNAM square sub-pattern are simply filled back to the original position, which may retard the reduction of the compression ratio. In the future, the research ordination is to propose a better inpainting method for these isolated point patterns and line segment patterns, aiming to improve the compression ratio without lowering the quality of restored images.

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