Fast Fractal Image Compression Algorithm Based on Compression Perception

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Abstract. To address the problem of long coding time of fractal image compression algorithm, this paper proposes a fractal image compression algorithm based on compression perception. Firstly, the algorithm is coded in the wavelet domain by separating the high and low frequency signals of the image, then, the low frequency information is fractally coded, while the sparse high frequency signals are sampled and coded in a compression-aware manner, and finally, a better image reconstruction compensation effect is achieved with the premise of reducing the number of coding searches and coding time. The experimental results show that this algorithm has a slight decrease in coding quality and compression ratio compared to fractal coding image compression, but has a superior improvement in coding speed.

Keywords: Image compression · Fractal coding · Compression perception · Wavelet transform

1 Introduction

Fractal images coding is an image coding strategy that takes advantage of the self-similarity of images of different scales and replaces the overall value domain block iterative search process of a series of radiometric transformations such as scaling, rotation and scale transformation of locally defined domain blocks, thus achieving a high compression ratio. However, there is a serious imbalance between the coding time and decoding time of fractal compression, and the improvement to decoding reconstruction quality is positively correlated with the coding time, making it difficult for fractal coding to meet the needs of practical applications. Therefore, how to achieve a better breakthrough in coding time and coding quality has become a key hot issue in the research of fractal image compression algorithms. Most of the current mainstream fractal image compression and coding optimisation algorithms are based on Jacquin coding scheme [1], and are mainly reflected on two aspects: firstly, in terms of coding speed improvement, there are mainly block classification strategies, fast search and other strategies, and

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secondly, in terms of image reconstruction quality improvement, there are mainly image block segmentation method improvements. The above methods can only improve the performance unilaterally, and there are few balanced performance optimisation solutions that combine both coding time and image reconstruction quality.

Fractal image compression coding can directly improve the coding speed. Guo Hui et al. used the value domain block variance as a classification index to improve the fractal coding process, and used the nearest neighbour search method to reduce the number of value domain blocks and definition domain blocks to be coded during the search process in order to shorten the coding time [2]. Zheng Yunping et al. proposed a fast fractal imaged compression algorithm based on an iteration-controlled search strategy [3], which controls the search process by using the number of fractal code iterations to remove invalid searches and inefficient searches, and ultimately achieves a significant increase in coding speed. Wang Li et al. proposed a fractal image compression algorithm based on center-of-mass features and important sensitive region classification [4]. The algorithm transforms the global search problem of R blocks in the codebook into a local fast search problem by constructing prime features, thus simplifying the block search process and achieving a reduction in coding time. Zhang Aihua et al. implemented a fractal image compression method based on sparse decomposition by processing the original image and combining it with relevant hardware execution structures [5].

Fractal image compression coding can also be combined with other algorithmic terms to improve the coding speed and quality. Lou Li et al. [6] proposed a hybrid coding algorithm based on the combination of wavelet and fractal. The algorithm performs wavelet decomposition of the image, encodes the low-frequency signal separately, and carries out fractal prediction based on the texture features of subgraphs in different directions, thus greatly reduced the fractal coding time. Zhang Aihua et al. [7] proposed a fractal image compression coding algorithm based on DCT compensation, which combines a fractal image compression coding method with a discrete cosine transforms approximation to find the best defined domain block and its mapping by adjusting the grey scale transform to achieve reconstruction image quality increment and reduce the coding time. Li-Xiu Wu et al. [8] proposed a generic reference-free stereo image quality evaluation algorithm using the quadratic tree wavelet transformed in order to effectively evaluate the quality of various types of distorted stereo images. He J et al. [9] used the characteristics of the human visual system to optimize the SNAMG segmentation method for images using visual thresholding on those and used it for adaptive sub-block segmentation of fractal image compression, which greatly improved the efficiency of the coding process.

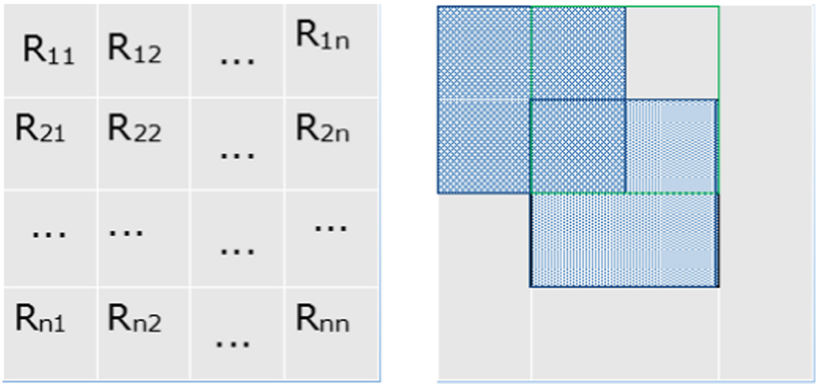
This paper proposes a fast fractal image coding algorithm based on compression-awareness. The algorithm makes full use of the characteristics of wavelet variations, firstly fractal coding the low frequency part of the wavelet transform as a way to reduce the coding time, and then sampling and coding the sparse data of the high frequency part using the compression-aware method, finally forming a hybrid image coding framework. Finally, the theoretical analysis and experimental results verify the superiority, robustness and efficiency of the method described in this paper.

2 Compression-Aware Fractal Image Compression Algorithm

Fractal image coding mainly uses the self-similarity of images at different scales in different regions to achieve compression, and when coding, the image is firstly segmented into fixed blocks to obtain the value domain R blocks and the definition domain D blocks, then the D blocks are shrunk in the spatial domain to obtain the codebook, and then the best matching D blocks are found for each R block and their fractal codes are recorded to obtain the iterative function system, and finally the decoding is based on the iterative function system and the fractal code iteration The decoded reconstructed image is obtained by iterative decoding based on the iterative function system and the sub-codes. Since each R-block searches for matching a large number of times, a long coding time usually occurs, so this subsection will first analyse the characteristics of the branching coding process, then introduce the wavelet transform into the branching coding strategy, and finally develop a hybrid coding and decoding scheme combining compression-awareness and fractal coding for the high and low frequency signal data obtained by the wavelet transform.

2.1 Optimisation of Fractal Coding Algorithms Based on Classification Methods

Fractal images coding uses the similarity in images of different scales in different regions to achieve compression. The coding process performs a fixed block segmentation of the image into a number of mutually non-stacked values domain blocks R blocks, then the image is segmented from left to right and from top to bottom by step B to obtain the corresponding definition domain D blocks, and the set of definition domain blocks is fractally coded between groups of codebooks Ω, as shown in the following Fig. 1.



(1) Segmentation of range block (2) Partition of domain block

Fig. 1. Schematic diagram of value domain block partitioning and definition domain block partitioning

The best matching block is selected as the ΔD block of the smallest mean square error in the codebook, and the one with the smallest error in the eight equidistant transformations Tq is selected as the equidistant transformation parameter, thus obtaining the best approximate solution to Ri. The overall transformation process is as shown in Fig. 2.

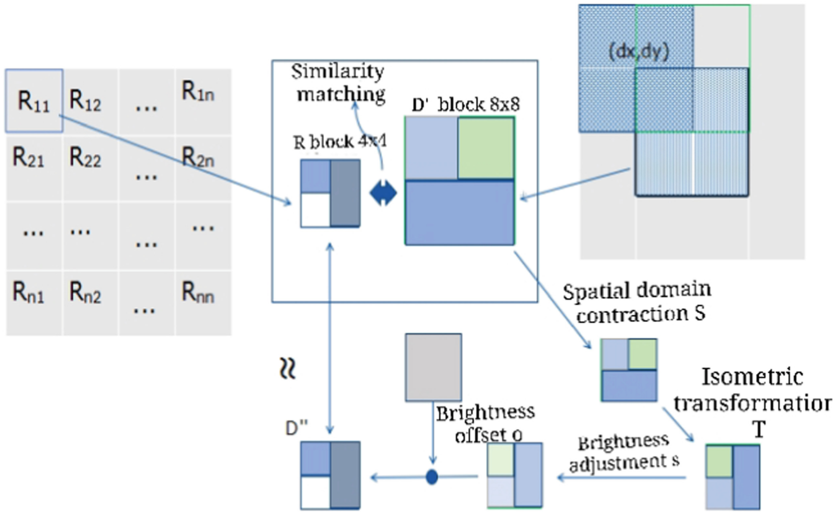


Fig. 2. Value domain block matching process for fractal image coding

Given the definition domain set Di and the range block RI, the brightness adjustment parameter Si in the process of distraction coding can be expressed as the following formula (1).

$$s_i = \frac{n\sum_{i=1}^{n} d_i r_i - \left(\sum_{i=1}^{n} d_i\right)\left(\sum_{i=1}^{n} r_i\right)}{n\sum_{i=1}^{n} d_i^2 - \left(\sum_{i=1}^{n} d_i\right)^2} \tag{1}$$

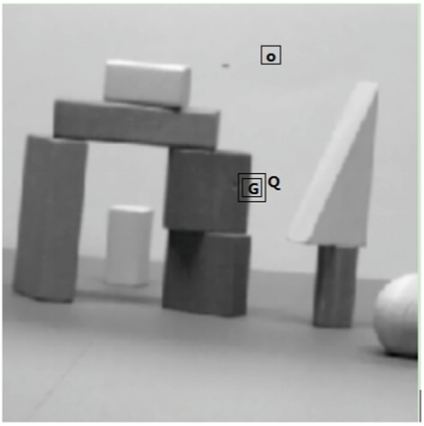
By the same token, the luminance offset parameter Oi in the fractal process can be expressed as shown in formula (2).

$$o_i = \frac{\left(\sum_{i=1}^{n} r_i\right)\left(\sum_{i=1}^{n} d_i^2\right) - \left(\sum_{i=1}^{n} d_i\right)\left(\sum_{i=1}^{n} d_i r_i\right)}{n\sum_{i=1}^{n} d_i^2 - \left(\sum_{i=1}^{n} d_i\right)^2} = \frac{1}{n}\left(\sum_{i=1}^{n} r_i - s\sum_{i=1}^{n} d_i\right) \tag{2}$$

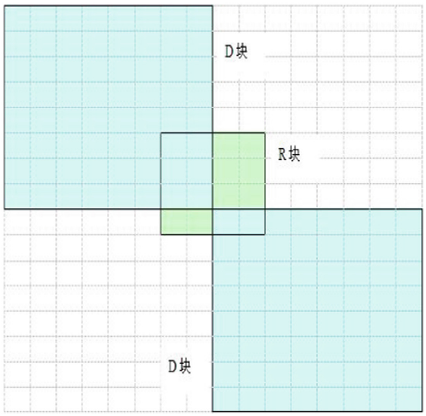
The mean squared error of Ri and Dj in the coding process can be expressed as shown in formula (3).

$$\min_{s_i, o_i \in R} f(s_i, o_i) = \frac{1}{n}\left[\sum_{i=1}^{n} r_i^2 + s\left(s\sum_{i=1}^{n} d_i^2 - 2\sum_{i=1}^{n} d_i r_i + 2\cdot o_i \sum_{i=1}^{n} d_i\right) + o_i \cdot \left(o_i \cdot n - 2\sum_{i=1}^{n} r_i\right)\right] \tag{3}$$

Fractal coding algorithms need to spend a lot of time for global search, however, the texture distribution of a large number of images shows a strong regional nature, as shown in Fig. 2 and 3, the pixels at point O in the image are relatively uniformly distributed and the pixels at point G have a large variation in texture. Therefore, the segmented value domain blocks R blocks can be classified according to their texture characteristics during fractal coding, i.e. blocks of uniform pixel distribution are classified as simple classes and blocks with large pixel variation are classified as complex blocks. By classifying the value domain blocks according to whether their mean squared deviation is less than a set threshold, and less than the threshold then the mean value is directly substituted for the best matching block search strategy. In addition, for most blocks similarly defined domain blocks D blocks usually exist in the vicinity of the value domain blocks R. By limiting the interval of the best search to the region near the value domain blocks R blocks, both can reduce the coding time.



a Classification of value field blocks



b Search range for value field blocks

Fig. 3. Fractal coding strategy for classification methods

This thesis adopts a priori strategy to define the classification threshold R = 6.0, and then calculates the mean square error of the value domain blocks R_{var} and constructs a classification basis to determine the classification match with the following formula (4).

$$R_{var} = \sqrt{\frac{1}{R \times R}(\sum_{x}^{R}\sum_{y}^{R}R_{xy}^{2}) - (\frac{1}{R \times R}\sum_{x}^{R}\sum_{y}^{R}R_{xy})^{2}} < 6.0 \tag{4}$$

The R blocks that satisfy the above conditions are simple blocks and their averages R_{ave} are saved and the averages are calculated as shown in formula (5).

$$R_{ave} = \frac{1}{R \times R}\left(\sum_{x}^{R}\sum_{y}^{R}R_{xy}\right) \tag{5}$$

Otherwise, a search for the best matching block in the restricted range is processed and the corresponding sub-code is saved.

2.2 Fractal Image Compression Algorithm Combining Compression-Awareness and Wavelet Transform

Wavelets has different scales of time-frequency resolution refinement characteristics, when in the centre of the higher frequency, wavelets in the time direction of the time frequency window becomes narrower, in the frequency direction of the time frequency window becomes wider, with very high time resolution; conversely, when in the low frequency centre, wavelets in the frequency direction of the time frequency window becomes narrower, in the time direction of the wider, with very high frequency resolution. Combining this with human visual features and applying it to image compression will give good results. The wavelet decomposition can be used for fractal coding by obtaining sub images of strong similarity in different spatial directions and at different resolutions. The wavelet decomposition is illustrated as shown in Fig. 4 and Fig. 5.

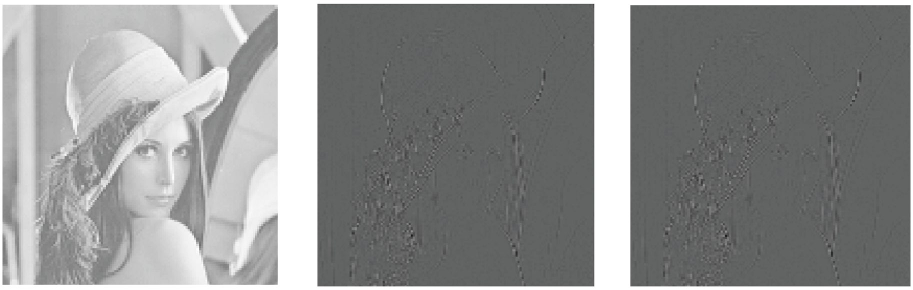
Combined with wavelet theory it can be concluded that the wavelet transforms does not achieve compression, but it is possible to reduce the coding time by coding only the low frequency part of the fractal image, and the high frequency parts will take compression perception of coding.

If the signal in a transformed domain is sparse or compressible, the original signal can be efficiently reconstructed by solving a convex optimisation problem by designing some kind of measurement matrix that is somewhat uncorrelated with the transform base, and this method is highly cost-effective in terms of compression because the length of the measurement matrix is much smaller than the length of the original signal. The high-frequency part of the image after wavelet transform is sparse, and the coding and decoding of the high-frequency signal by means of compression-awareness can effectively improve the efficiency of coding compensation.

The theory of compressed sensing to consists of three main components: the sparse representation of the signal, the selection of the measurement matrix and the design of the reconstruction algorithm. Firstly, the sparse representation capability of the transform base is measured by the sharp decay of the transform sparse, and a suitable transform

(1) Schematic diagram of WTD1 (2) Schematic diagram of WTD2 (3) Schematic diagram of WTD3

Fig. 4. Schematic diagram of wavelet transform decomposition



(1)LL1 (2)HL1 (3)HH1

Fig. 5. Subplots in different directions

base is selected to represent the signal, maintain efficient sparsity and achieve high accuracy decoding and reconstruction capability. Then, by projecting the sparse signal onto an observation matrix that is disjoint from the transform base, the Gauss matrix with finite isometric Rip is selected as the measurement matrix to achieve the effect of data acquisition and compression by satisfying $(1-\delta_K)||x||_2^2 \leq ||\phi x||_2^2 \leq (1+\delta_K)||x||_2^2$ when solving parameter $\delta_K < 1$. Finally, the signal is reconstructed by solving for the optimal solution $\alpha^{'} = \min ||\alpha||_{l_0} \quad s.t. \quad y = \phi\, \psi \alpha$ to the L0 parametrization.

The steps of the fractal image compression algorithm based on the combination of compression perception and wavelet transform are as follows.

Input: image to be encoded orig, measurement matrix φ.

Output: decoded reconstructed image res.

Step 1. Perform db97 wavelet transforms into the input image to be encoded and save the low-frequency submap LL and the high-frequency submaps in three different directions of horizontal and vertical details.

Step 2. Perform fractal encoding of the low-frequency submap LL, record and save the fractal code, and use the fractal code to iterate to obtain the reconstructed low-frequency submap LL′.

Step 3. Calculate the low frequency difference subgraph $\mathrm{LL0} = \mathrm{LL} - \mathrm{LL}'$.

Step 4. Construct a sparse sparse subgraph based on the difference subgraph of the low-frequency part with the high-frequency subgraphs in three different directions matrix.

Step 5. The reconstructed coefficient matrix is decomposed at 5 levels using the db97 wavelet to obtain the sparse matrix x, and project the sparse matrix onto the measurement matrix φ to obtain the observation matrix $y = \varphi x$.

Step 6. The sparse matrix is reconstructed with high probability of a small number of measurements y using OMP's improved arithmetic subspace tracking algorithm SP.

Step 7. The compression-aware reconstructed sparse matrix is inverse sparse transformed, i.e., a 5-level inverse db97 wavelet transforms is performed to obtain the reconstructed coefficient matrix M', and it is fused with the reconstructed low-frequency subgraph LL' of the fractal encoding wait to obtain the matrix $M1 = M' + LL'$.

Step 8. fuse the matrix M1 and perform the inverse wavelet transform to obtain the reconstructed image res.

3 Experimental Results and Analysis

In this thesis, representative images of different scenes such as animal (Figure a), plant (Figure b), landscape (Figure c), geometric (Figure d) and medical (Figure e) were selected. The computer configuration was Win7 flagship and above, Intel (R) core CPU @2.60 GHz i5-3230M 2.60 GHz, 4.00 GB of memory (RAM), 64-bit operating system, Matlab 7.0 integrated development environment.

The images and results of the experimental tests are as shown in Fig. 6.

(a)Animal drawings (b)Botanical drawings (c)Landscape drawings (d)Geometric drawings (e)Medical diagrams

Fig. 6. Test image data

Aiming at the above images, this paper systematically verifies the relevant performance of basic fractal algorithm, fractal combined wavelet and compression aware fractal image compression from three aspects: compression ratio (C), running time (time) and peak signal-to-noise ratio (PSNR) [as shown in formulas (6) and (7)].

Compression ratio (C) is the ratio of compressed data size (CDS) to pre compressed image size (SIC). The calculation formula is shown in formula (6):

$$C = \frac{CDS}{SIC} \tag{6}$$

Subjective fidelity is to judge the reconstruction quality of the image by human eye judgment, while objective fidelity usually takes the peak signal-to-noise ratio (PSNR) as the evaluation criterion. The formula of signal-to-noise ratio is shown in formula (7):

$$PSNR = 10\log\frac{255^2}{MSE}(db) \tag{7}$$

In formula (7), MSE is the pixel error between the original image f (x, y) and the reconstructed image f (x, y)′, and the calculation is shown in formula (8):

$$MSE = \frac{1}{MN}\sum_{x=0}^{M}\sum_{y=0}^{N}\left(f(x,y) - f(x,y)'\right)^2 \tag{8}$$

The experimental comparison parameters are shown in the table below (Table 1):

Table 1. Algorithm comparison experimental parameters table

Image	Experimental parameters	Basic fractal algorithm	Fractal combined with wavelet algorithm	Compression-aware fractal image algorithm	Acceleration ratio compared to basic algorithm
Bird	Time/s	2967.76	1.05	1.31	2256.67
	Psnr/db	39.10	29.82	32.56	
	C	4.74	17.65	2.87	
Rose	Time/s	3500.17	0.99	1.06	3301.88
	Psnr/db	35.58	27.76	31.38	
	C	4.74	17.65	2.92	
Visible	Time/s	2964.85	1.81	2.04	1453.35
	Psnr/db	35.77	26.30	30.71	
	C	4.74	17.65	2.811	
Shape	Time/s	2969.82	1.04	1.24	2395.01
	Psnr/db	38.33	34.27	39.25	
	C	4.74	17.65	2.90	
Heci	Time/s	3933.01	0.88	1.10	3543.57
	Psnr/db	31.98	30.12	35.18	
	C	4.74	17.65	2.91	

The above experimental results show that in terms of coding time, as this algorithm combines the advantages of fractal, wavelet coding and compression-aware coding, although there is a slight increase in coding time compared to the fractal combined with wavelet algorithm, the fractal combined with wavelet is inferior to the algorithm described in this paper in terms of image restoration quality, and the time efficiency is about 1000 times faster compared to the basic fractal coding. In terms of image quality restoration, the algorithm in this paper is based on fractal combined wavelet coding of high-frequency subgraphs and low-frequency difference maps, and its decoding and reconstruction quality is much better.

4 Conclusion

Compared with the basic fractal coding algorithm, the coding speed is greatly improved with a slight decrease in decoding quality; compared with the fractal combined with wavelet coding method and the compression-aware coding method, the coding time is slightly longer but the restored image quality is higher. Therefore, the algorithm in this paper can guarantee the decoding image quality while shortening the fractal coding time, which is of practical significance to the popularization of fractal image coding methods.

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