Research on adaptive fractal image compression algorithm based on flexible classification technology

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Abstract. This paper proposes a flexible classification technique for accelerating image matching and improving coding quality, using a fast adaptive fractal image compression method with four fork tree as image division and flexible classification technology, which is a kind of pre-segmentation of images. With using the self-similarity of each part of the image, the fractal encoding is carried out. In order to reduce the encoding time to dozens of seconds, it eliminate the block effect and realize the fast fractal coding of color image, so as to speed up the encoding speed and further improve the image comprehensive performance of compression ratio and signal-to-noise ratio/encoding time.

1. Introduction

It is not difficult to analyze the implementation process of strict 72 classifications, it reflects the image. The matching between the source blocks actually pays more attention to the local characteristics of each object in the image block. When the sub-fast size is small, the brightness and brightness change has a good approximation. With the increase of the sub-fast size, the difference between local and global features cannot truly reflect the degree of suitability between image block R and source block D.

In order to improve the coding effect, it is necessary to introduce flexible classification technology. By the technology, we can find a matching method, which can change with the size. We can construct the sequence of deformation and corresponding classification and isometric transformation and increase the probability of source block matching, so as to have more beneficial approximation block objects, such as to improve image quality, increase the compression ratio and reduce the bit rate.

Finally, the research goal of this project is to obtain a fast fractal image compression algorithm based on the adaptive characteristics of flexible classification.

2. Fractal Image compression method

Many important local features in the image, such as linear segment, equivalent grayscale region, remain constant at different scales. The grayscale variation region of the constant gradient is only a constant number of times at different scales. These redundant performance on image expression can be identified and eliminated by the block fractal image compression algorithm based on PIFS.

The basic block fractal compression method is to divide the elements in a complete metric space H(the image to be encoded) into a set of non-overlapping image blocks and another set of overlapping image blocks of the set \( D = \{ D_i \mid i = 1,2,...,M \} \). That is, \( I = \bigcup_{i=1}^{N} R_i = \bigcup_{i=1}^{M} D_i \), \( R_i \cap R_j = \emptyset \ i \neq j \). Where in, each element of R represents a block (Range Block), each element of D represents the source block...
(Domain Block) $\mathbf{D} \geq \mathbf{R}_i$. With $\mathbf{D}$ as a codebook, for any one image block $\mathbf{R}_i$ searched in $\mathbf{D}$ with the closest source block $\mathbf{D}_i$, the best match $(\mathbf{R}_i, \mathbf{D}_i)$ determines that a shrinkage factor is an affine transformation $\mathbf{R}_i \simeq \mathbf{w}_i(\mathbf{D}_i)$. By the final $n$ affine transform $\mathbf{w}_i$ ($i=1, 2, \ldots, N$) can define the shrinkage transformation $\mathbf{w}(\cdot) = \bigcup_{i=1}^{n} \mathbf{w}(\cdot)$, its shrinkage factor $s = \max \{s_i\}$. $W$ forms the fractal encoding of image $\mathbf{I}$. In practice, $\omega_i$ is composed of basic transformations such as geometry and grayscale into, $\tilde{\mathbf{R}}_i = \mathbf{w}_i(\mathbf{D}_i) := \alpha_i l_i (\mu_i(\mathbf{D}_i)) + \beta_i$. where $\mu_i$ is a spatial shrinkage transformation and $l_i$ is one of eight possible isometric mappings, $\alpha_i$ is the image contrast reduction factor, $\beta_i$ is the brightness offset of the image. The optimal matching coefficient depicted by $\omega_i$ refers to the MSE distance minimum. $\max_{i=1}^{M} d(R_i, \tilde{R}_i) := \frac{1}{|R|} \sum_{j=1}^{|R|} (R_{i,j} - \tilde{R}_{i,j})^2$, a block $\mathbf{R}_i$ and its approximate $\tilde{\mathbf{R}}_i$, wherein, the number of pixels $|\mathbf{R}_i|$ like a block. $W$ is a shrinkage transformation in a complete metric space, by the Banach point theory, $W$ has a unique fixed point $A$, $A = W(A)$, and for any initial set $B$, after countless iterations, it will converge to $A, A = \lim_{n \to \infty} W^{(a)} B, W^{(0)} (B) := B, W^{(a+1)} (B)$. A can be regarded as the approximation of the original image. Applying this set of transformations to any of the initial images at the decoding end, the fixed point that can be obtained by iteration is the decoding image similar to the original image.

3. Fast Adaptive fractal image compression algorithm
The key of fractal image compression is to construct shrinkage affine transform $\mathbf{w}_i$. Given the image block $\mathbf{R}_i$, turn it into a search for the appropriate source block $\mathbf{D}_i$ in $\mathbf{D}$.

3.1. Image partitioning
Image partitioning determines the total bit rate of image encoding (determined by the number of pixels), which has a great influence on the coding quality. The traditional fractal image compression algorithm has square division, triangular division and rectangular division of the original image. For example, block fractal encoding algorithms typically use fixed-size image blocks and source blocks, and at best extend only two sizes. This fixed-size image partitioning method cannot make full use of the content of the image, lack of self-adaptability to the encoded object. The reason is that self-similarity does not necessarily exist between image blocks divided into some fixed format. Therefore, for some images, it may not be possible to find a suitable source block at all, so that the approximate error satisfies the given threshold range. If the transformation was established by force, it will inevitably bring about the reduction of image quality. For the change is relatively flat, self-similar features are more obvious large area of the image, fixed size division and need to use more than one more image block to cover it, the corresponding increase in the number of basic affine transformation. Obviously this does not conform to the original intention of image compression. Therefore, we should look for an adaptive image partitioning method to divide the encoded objects into images, which can obtain better coding results.

Through the analysis, we can know that in the field of image processing, quad-tree has the adaptive characteristics of image division. According to the consistency determination condition of the image, the image can be segmented recursively. If the image block of a layer does not meet the consistency determination condition, it can be extended on this branch of the four-fork tree corresponding to the image, with representing $\mathbf{R}$ with four sub-diagrams of $\mathbf{R}$. Finally, the image block corresponding to the leaf node of the quad-tree is either satisfied with the consistency determination condition, appears at a higher level, or reaches the predetermined maximum decomposition depth, which is already the minimum size image allowed.

Because the quad-tree has the characteristics of adaptive image segmentation, many block fractal image compression algorithms use it to generate like block set $\mathbf{R}$. This project is intended to use the image division method of four fork tree. Whenever the sub-image as a quad-tree expansion, as long as the maximum decomposition depth is not reached, the meaning of the output symbol '1', which represents the first level of image division. If one of the quad-tree is no longer stretched, the output
symbol ‘0’, which indicates that the image partition has stopped. At this point, the consistency determination condition refers to finding the source block \( D_i \in D \), and the approximate error of the transformation result \( w_i(D_i) \) and \( R_i \) is less than the given threshold.

3.2. Calculation of related transform parameters

When the block \( R_i \) is matched with the source block \( D_i \) after shrinkage and isometric transformation, the introduction of parameter \( \alpha_i \) and \( \beta_i \) can adjust the contrast and brightness, and provide a richer candidate matching object for. Assuming \( R_{i,j} \) and \( D_{i,j} \) represent the J pixels of \( R_i \) and \( D_i \) respectively, the approximate mean square error is.

\[
d_i = \frac{1}{|R_i|} \sum_{j} \left( \alpha_i \cdot D_{i,j} + \beta_i - R_{i,j} \right)^2
\]

\(|R_i|\), is the number of the number of pixels in the image block \( R_i \). When \( d_i \) is a minimum, the parameter \( \alpha_i \), the \( \beta_i \) value can be obtained by making.

\[
\begin{align*}
\frac{\partial d_i}{\partial \alpha_i} &= \frac{2}{|R_i|} \sum_{j} \left( \alpha_i \cdot D_{i,j} + \beta_i + R_{i,j} \right) \cdot D_{i,j} = 0 \\
\frac{\partial d_i}{\partial \beta_i} &= \frac{2}{|R_i|} \sum_{j} \left( \alpha_i \cdot D_{i,j} + \beta_i - R_{i,j} \right) \cdot D_{i,j} = 0
\end{align*}
\]

As long as \( |\alpha_i|<1 \) is guaranteed, the iterative decoding process will converge to the absorption factor. There is a mean square root error \( mms = \sqrt{d_i} \) given in the similarity measure between the image blocks.

3.3. Rapid matching technology

The main reason for the lengthy encoding time of fractal images is to find the best source block and image block matching. In order to reduce the number of test gamete images, a variety of fractal image compression algorithms are limited or some classification techniques are used. For example, there are common values, texture lines and other characteristics of the classification of images. Jacobs and others according to the image block four corners of the brightness, brightness changes will be incorporated into one of the 72 categories. Only consider the same kind of image, source block matching. This project study is based on the selection of 72 types of taxonomy.

3.3.1. 72 types of taxonomy

According to the brightness of four blocks \( I(i) \) in image block I and the arrangement of \( A(i) \) and brightness change \( V(i) = \{i=1,2,3,4\} \), the 72 classification classifies I as primary and secondary two. The size of \( I \) is \( 2^{2n} \times 2^{2n} \), the subscript of the pixel is \( j, k \), and the sub-blocks are.

\[
A(i) = A(i) = \sum_{j=1}^{2n} \sum_{k=1}^{2n} I(i)_{j,k} \quad V(i) = \sum_{j=1}^{2n} \sum_{k=1}^{2n} I^2(i)_{j,k} - A(i)
\]

The main classification divides all its possible permutations into three equivalent classes in the order of \( A(i) \) from large to small. The elements of each equivalent class are considered the same under eight possible isometric transformations. The auxiliary classification is based on the main classification. the arrangement of \( V(i) \) first implements the isometric transformation. It was divided into three equivalent classes according to the arrangement of the results (the same as the main classification). In this way, any one image block I by the main, secondary two classification will obtain one of the \( 3 \times 8 \times 3 = 72 \) class number, but also determined to transform its brightest block to the first isometric transformation number.
3.3.2. The flexible classification technology
Under normal circumstances, the more source block D involved in the test, the more likely it is to get a good approximation like block R, the appropriate time is lengthened. Conversely, limiting matching can shorten the matching time, but the matching accuracy will be affected. When using the Image Adaptive encoding algorithm of four-fork tree, whether the matching is limited will affect the change of image quality and compression ratio. A good match can slow down the growth of the quad-tree and improve the approximate accuracy.

As can be seen from the class 72 taxonomy, the brightness of the block I(i) and the values of A(i) and the Brightness Change V(i) play a decisive role in the classification of I. They reflect the overall characteristics of each child block I(i). However, the matching between the elephant and the source block actually pays more attention to the local characteristics of each corresponding pixel in the image block. That is, when the size of I(i) is small, A(i) and V(i) are also good approximations of this local feature. As its size increases, the difference between local and global features increases. A(i) with A(j) (or V(i) and V(j)) The small differences between them are not sufficient to reflect the corresponding changes in the local characteristics of I. In this way, the 72 types of master-secondary classifications strictly in accordance with the values of A(i) (or V(i)) often do not fully and truthfully reflect the degree of suitability between the image block R and the source block D.

In order to improve the coding effect, we should try to change the shortcoming of this strict classification method. In order to prepare a richer and more effective matching candidate object for the image block. Encoding increases the number of candidate matching objects caused by classification technology, does not increase the encoding of the bit rate. It does not have any impact on the decoding program, only needs to be the encoding time and encoding income two factors of the trade-off.

Through the analysis and research, a flexible classification technique is used to classify the source block D. The technique is not to give the unique classification and isometric transformation according to the absolute value of A(i) or V(i), but to find a threshold delta which can change with the size, and to construct the threshold calculation method. When the \(|A(i) - A(j)| < \delta \) or \(|V(i) - V(j)| < \delta^2\), the sequence of deformation is produced and the corresponding classification and isometric transformation. In this way, for some modules, there may be several category numbers and isometric transformation. The source block is also equivalent to appearing in multiple matching candidate sets. When matching, like blocks will have more beneficial approximation objects, and not in the same way as the full space search, too much unnecessary trial matching. Using flexible classification technology, it is expected to improve image quality and reduce the bit rate under the premise that the encoding time has not increased significantly.

3.3.3. Accelerating technology
The main reason for the lengthy fractal encoding time involves too many sources, a large number of floating-point operations in the process of image block fitting and trial matching. In addition to using flexible classification technology to speed up the coding process, the project also proposed to use a number of other acceleration technology.

One-time construction to reduce the image I' and the corresponding source block matching candidate set, in order to avoid the same source block in multiple trial distribution of the calculation and classification overhead.

Before the Test match, the brightness and the square of brightness and the common items are calculated at one time. Only the crossover and final errors of the source block are calculated.

We can adjust the isometric transformation number of the source block and the image block, and change the calculation method of the isometric change.

4. Algorithm
According to the input image I and approximate error threshold data, the output of a set of shrinkage affine transformation coefficients of the file IFS.
Method steps:
(1) Sampling I to obtain a $2^{N-1} \times 2^{N-1}$ reduction image $I'$.

(2) Set the window size, from $2^{N-1} \times 2^{N-1}$ to $2^n \times 2^n$, in $I'$ sliding, get the image block in the window $I_D'$. A flexible classification is used in the $I_D'$, we can get its category number set $\{d_1, d_2 ... d_k\}$, and then $I_D'$ is added to the corresponding category $D_k$ matching candidate set D respectively.

(3) The first I is divided into two levels of four forked trees, the resulting image block into the stack R.

(4) If the stack R is not empty, the loop from R ejected element R. The R by 72 categories classification, get the category number. From the matching candidate set D to take the same source block of the collection $D_i$, each element of $D_i$ loop, According to R and $D_i$ isometric transformation number. The actual isometric transformation $D \leftarrow I(D_i)$, according to R and D calculation of the best parameters $\alpha$, $\beta$, is calculated. By $\alpha$, $\beta$ approximate mean square root error RMS, recording the minimum mean square root difference $r_{\min}$ and the corresponding $j_{\min}$, $\alpha_{\min}$, $\beta_{\min}$, $\gamma_{\min}$. If $\gamma_{\min} < tol$ or R is already $2^n \times 2^n$ the image block, it will be $j_{\min}$, $\alpha_{\min}$, $\beta_{\min}$, $\gamma_{\min}$ pushed to the file IFS. Otherwise, R will be divided as a quadtree, and its four components will be pressed into the stack R at a time.

5. Conclusion

Experimental results show that the effect of encoding acceleration using this algorithm is obvious. With the use of flexible classification technology, compared to the strict 72 encoded classification, the image quality improvement was about 0.5dB, while the coding time did not increase significantly.

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