Image Compression based on Iteration-Free Fractal and using Fuzzy Clustering on DCT Coefficients

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Abstract: *In the proposed method, the encoding time is reduced by combining iteration-free fractal compression technique with fuzzy c-means clustering approach to classify the domain blocks. In iteration-free fractal image compression, the mean image is considered as domain pool for range-domain mapping that reduces the number of fractal matching. Discrete cosine transform (DCT) coefficient is used as a new metric for range and domain blocks comparison. Also fuzzy clustering approach reduces the search space to only a subset of domain pool. Based on Fuzzy clustering on DCT space, the domain pool is grouped into three clusters and the search is made in any one of the three clusters. The proposed method has been tested for various standard images and found that the encoding time is reduced about 42 times than the iteration-free fractal coding method with only a slight degradation in the quality of images.*

Keywords: *Fractal image compression, fuzzy clustering, DCT coefficients, contractive affine transformation.*

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1. Introduction

Fractal Image Compression (FIC) is a technique to store images in small amount of space. It mainly considers the self-similarity property that occurs in most real world images. The concept of fractal coding was initially proposed by Barnsley [1] and extended by Jacquin [10] based on Partitioned Iterated Function system (PIFS). Conventional FIC is computationally exhaustive. Using contractive affine transformation [11], for each range block a most similar domain block is to be searched from the domain pool. Most pure fractal-based encoding schemes does not achieve good results in encoding time, but hybrid schemes combining fractal compression and alternative techniques have achieved considerably good results. Various methods have been suggested in literature to speed up the encoding process.

Many classification or clustering approaches was also applied to organise the domain pool into various groups [8, 14, 19]. Image blocks are classified based on the properties of edges [8]. Kovacs classification scheme [14] is based on direction of the first approximate derivative and the root-mean-square (RMS) error. Another classification approach that groups the domain blocks based on standard deviation is proposed [19], where the search is restricted to domain blocks of similar standard deviation. Some of the fast FIC schemes are proposed on considering the spatial correlation [17] in both the range blocks and domain blocks.

A hybrid fractal/DCT image compression technique is presented in [7, 15]. Methods for fractal coding based on excluding the domain blocks in order to limit the search process [16] and procedure based on no search technique are proposed [9, 18]. The no search procedure based on grey-level transform proposed by Wang et al. using a fitting plane is very fast and reduces the matching error [18]. Most of the proposed FIC techniques are fast but the quality of the reconstructed image is not satisfactory.

In this paper, the iteration-free fractal compression is followed which eliminates the iterations in decoding process of basic FIC. Also the mean image where the features of the original image are preserved is considered as domain pool. The domain pool of reduced size thereby reduces the search for the best matching domain blocks. In the proposed method, the image is converted from pixel space to DCT space. Then fuzzy clustering is applied to cluster the domain blocks calculating the cluster center for each group and error between range and domain blocks are calculated based on DCT coefficients [12]. The search for matching domain block for each range block is limited to one of the cluster. The compression time is greatly reduced in this method while preserving the quality of reconstructed image.

2. Partitioned Iterated Function System

In the PIFS proposed by Jacquin [11], the image is divided into non-overlapping square blocks called range blocks. The larger overlapping blocks called domain bocks are obtained by partitioning the same image to construct the domain pool. Considering any one range block *R* there is most likely another part of the image, may be larger domain block D that is similar to range block R at least after some transformations. Mapping of range block to a similar domain block is performed using affine transformation [11] given as follows:

$$\hat{R} = i\{\alpha\left(SoD\right) + \delta\} \tag{1}$$

Where S denotes the operation to contract the domain block to the size of the range block, $\hat{R}$ is the coded range block, i represents isometric transformation, α represents contrast scaling, δ is the luminance shift and D is the matching domain block for the range block R. In order to minimise the error between the range block and domain block various possible transformations are performed and any of the following isometric transformations:

1. Identity (i.e., no transformation).
2. Reflection about mid-vertical axis of the domain block.
3. Reflection about mid-horizontal axis of the domain block.
4. Reflection about first diagonal of the domain block.
5. Reflection about second diagonal of the domain block.
6. Rotation around center of the domain block, through +90°.
7. Rotation around center of the domain block, through +180°.
8. Rotation around center of the domain block, through -90°.

Thus, any range block is represented by a domain block after suitable transformations. That is, the range block R is coded by the following parameters:

1. x, y coordinates of the domain block that matches with the range block (after suitable transformations).
2. Isometric transformation index, i, i=1, 2, …, 8. For example, isometric transformation index i=1 indicates identity transformation; i=2 indicates reflection about mid-vertical axis and so on; i=8 indicates rotation around the center of the block through -90°.
3. Contrast scaling, α.
4. Luminance shift, δ.

These parameters are called the fractal code.The entire image is represented by the fractal codes for all the range blocks of the image. The memory space required to store these parameters is much less than the space needed to store. In the above fractal compression process the most time consuming step is mapping the range block to an equivalent domain block. Also in the compression process to find out the appropriate domain block for a range block, pixel-to-pixel comparison is performed which takes considerably a large amount of time. This paper mainly concentrates in reducing the encoding time and also the iterative decoding process is simplified.

3. Proposed Method

The excessive encoding time is required in conventional FIC due to exhaustive search process for range-domain mapping. Reduction in domain pool size and clustering domain blocks into groups thereby reducing the number of fractal matching can significantly reduce the encoding time. Iteration free scheme is combined to further simplify the decoding process. Fuzzy clustering approach is applied for domain blocks classification and pixel values of image blocks are converted to DCT coefficients. Thus iteration free procedure for FIC based on fuzzy clustering using DCT coefficients is proposed.

The iteration-free method of fractal coding proposed by Chang and Kuo [4, 5] basically makes use of the mean image computed from the original image. Mean image is constructed by computing the mean of all the range blocks. This is used as the domain pool. Due to the fact that most parts of the blocks overlap in the mean image, the neighboring blocks have high similarity. This overlapping produces redundancies between the domain blocks. The block averaging method can reduce those redundancies. Hence, the coding performance will be improved compared with the conventional fractal schemes. The compression process starts with classifying the range blocks to be uniform and rough block based on variance. If the range block is a uniform block it will be coded by mean of the range block, otherwise the following contractive affine transformation is applied to get the matching domain block:

$$\hat{R} = i\{\alpha(D - \mu_D) + \mu_R\} \tag{2}$$

Where $\hat{R}$ is the domain block that matches with the range block after the transformation, D is any domain block, μ_R is the mean of range block, μ_D is the mean of domain block, α is the contrast scaling, and i is the isometric transformation index.

An iteration-free technique is made use of to proceed in the decoding stage. As coding of the fractal image is done with the mean image, during the decoding phase the mean image is also transmitted along with the fractal codes. To decode and obtain a particular range block of the reconstructed image, the corresponding domain block from the mean image is taken and the contractive affine transformation denoted by the fractal code is applied on it. This gives the required range block of the image in one stroke, without any iteration. Other range blocks of the image are obtained in similar manner; the decoding time is drastically reduced. The block diagram of iteration-free FIC process is shown in Figure 1. In the encoding stage, the input $M \times M$ image is partitioned into non-overlapping blocks called range blocks R_i of size $B \times B$. The mean image is constructed by calculating the mean of each range block. Mean of range blocks together represent the mean image of size $M|B \times M|B$. This mean image is used as the domain pool which is partitioned into domain blocks D_j. For each range block, matching domain block is obtained using contractive affine transformation is given in (2). Finally fractal code is found using the matching domain block which is considered as compressed coded file. Then mean image and fractal codes are stored as the representation of the compressed image. In the decoding stage, the mean image is obtained from the compressed image. For each range block, the fractal code is obtained. Then the scaling and rotations are applied to the position of the mean image. Thus the decompressed image is reconstructed by decoding each range block with fractal codes.

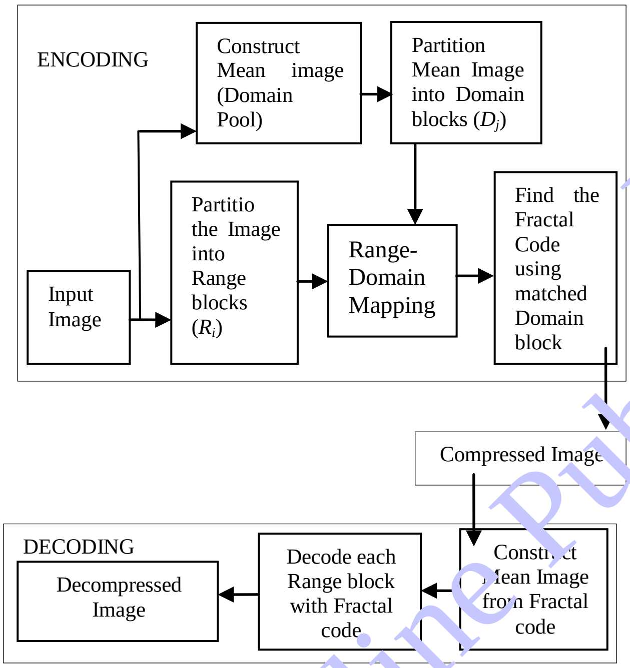


Figure 1. Block diagram of iteration-free fractal image compression.

4. Fuzzy Clustering on DCT Coefficients

The clustering algorithm is another solution to reduce the encoding time of fractal coding. Further computational complexity can be reduced when the image is converted from pixel space to DCT space.

4.1. Fuzzy Clustering

Fuzzy c-means algorithm [3] is the most famous method that introduces the concept of fuzzy sets which deals with vague concepts. In fuzzy c-means algorithm, each data element may belong to more than one cluster based on degree of membership associated with each element. The fuzzy c-means method extends the concept of K-means [2] algorithm by presenting the model of fuzzy sets. The proposed iteration-free fractal coding scheme is combined with fuzzy clustering approach to enhance the performance. Fuzzy c-means method is a process of calculating degree of membership for each data element and then using this membership function, data elements are assigned to one or more clusters. The membership function is usually defined on the basis of a distance function that is domain blocks in close proximities are grouped within the same cluster. The degree of membership for each domain block can take any intermediate values in interval [0, 1]. Let X_i $(x_1, x_2..., x_N)$ denotes set of N domain blocks. To partition this domain blocks into C clusters, the following cost function J should be minimised in each iteration of the fuzzy c-means algorithm:

$$J = \sum_{i=1}^{N} \sum_{j=1}^{C} u_{ij} \left\| x_i - c_j \right\|^2 \tag{3}$$

Where N is the number of domain blocks, C represents the number of clusters, c_j is the j^{th} cluster centre and u_{ij} is the degree of membership of domain block x_i in cluster j. The norm $\|x_i - c_j\|$ calculates the similarity of the domain block x_i to the cluster centre c_j. That is it measures the distance between the domain block and the cluster centre since distance is considered as membership function. The probability that a domain block belongs to a specific cluster is represented by the membership function. Here the probability is based only on the distance of image blocks from cluster centre. In each iteration, the fuzzy c-means algorithm calculates centre for each cluster and membership function for each block. For each block x_i, the degree of membership in cluster j is updated as follows:

$$u_{ij} = \frac{1}{\sum_{k=1}^{C} \left(\frac{\left\| x_i - c_j \right\|}{\left\| x_i - c_k \right\|} \right)^{\frac{2}{m-1}}} \tag{4}$$

Where m represents fuzziness coefficient. It measures the acceptance of the clustering into required groups and maintains the fuzziness of the resulting clusters. The cluster centre c_j is updated as follows:

$$c_j = \frac{\sum_{i=1}^{N} u_{ij} x_i}{\sum_{i=1}^{N} u_{ij}} \tag{5}$$

Where u_{ij} in the above equation represents the degree of membership value calculated in the preceding iteration. Initially the degree of membership value for block i to cluster j is assigned with a random value. When the fuzzy clustering algorithm is performed on DCT coefficients than the pixel values of image, the computations can be made easier.

4.2. Converting to DCT Space

Transformation maps the pixel values of an image to a set of transform coefficients. This coding is done on the consideration of correlation of pixels in an image with their adjacent pixels. Thus the value of pixel can be predicted from its neighbouring pixel due to the correlation between them. The elimination of redundancy between the pixel and its neighbouring pixel in an image is the main advantage of transformation. Thus transformation converts correlated data into transform coefficients that are uncorrelated. These uncorrelated coefficients can be processed independently. Decorrelation and energy compaction are the important properties of image transformation. Discrete cosine transform (DCT) has been widely used in many applications because of its ability to compact information to a high extent and decorrelate the image in most efficient way. The energy is packed within the large number of low frequency coefficients due to the energy compaction property and hence small high frequency coefficients are eliminated. Hence DCT performs image transformation at high speed with fewer computations.

Fractal coding with DCT transform have produced better results in previous efforts [20, 21]. DCT coefficients are calculated for each range and domain blocks so that image is converted to DCT space. All the further process on range and domain blocks uses only DCT coefficients. The one dimensional (1D) DCT transform for an image block of size $n \times n$ can be obtained after reshaping it into an 1D array. DCT transform is performed on image blocks using the following equation:

$$F(k) = w(k)\sum_{i=1}^{N} f(i)\cos\left(\frac{\pi(2i-1)(k-1)}{2N}\right) \qquad (6)$$

Where k = 1, 2, ..., N and $N = n \times n$

$$w(k) = \begin{cases} \frac{1}{\sqrt{N}}, & k = 1 \\ \frac{\sqrt{2}}{N}, & k \neq 1 \end{cases}$$

Therefore, N DCT coefficients are obtained on applying DCT transform on an array containing N elements. The average value of the block is represented by the first coefficient called DC coefficient. Thus, DC coefficient cannot be used for block comparison. The part of Equation 2, $\sum_{i=1}^{N}\cos\left((\pi(2i-1)(k-1))/2N\right)$, constitutes the cosine basis function. For various values of K, cosine basis function can be pre-computed and then multiplied with the values of *f(x)* which changes in each sub-sequences. Thus mathematical operations are reduced which simplifies the computations. Applying fuzzy clustering on DCT coefficients of image blocks results in high PSNR value and high speed-up factor when compared to fuzzy clustering on pixel space [12].

Several block-comparing method based on DCT coefficients have been proposed previously [6, 13]. In the proposed method, a metric which computes the error between domain and range blocks using DCT coefficients is defined as follows:

$$Error_{DCT}(R, D) = \sum_{i=2}^{N}\left|R_i - D_i\right| \qquad (7)$$

The value of the metric for i = 1 represents the average value of the sequence. Hence it is not considered for error calculation. This block comparing method performs only two operations such as subtraction and taking the absolute value. Less number of operations consequently speeds up the encoding process.

4.3. Proposed Method for Coding Process

The iteration-free fractal coding process by applying fuzzy clustering on pixel space can accelerate the encoding process. The proposed method of iteration-free FIC using fuzzy clustering on DCT coefficients speeds up the encoding process and also maintains the quality of reconstructed image.

The steps on how the proposed encoding method is implemented are as follows:

1. Input an image of size $M \times M$.
2. Partition the input image into non-overlapping range blocks of size B × B.
3. Find the mean of each range block. Mean of range blocks together represent the mean image of size $M|B \times M|B$. This mean image constitutes the domain pool.
4. Divide the mean image into domain blocks of size B×B which is same size as range block.

Consider input image of size 256 × 256 and the size of range blocks is 4 × 4, then mean image is of size 64 × 64. Assume domain blocks of size 4 × 4.

5. Reshape range and domain blocks into 1D array and calculate 1D DCT coefficients that results in 16 DCT coefficients for each range block (R_{DCT}) and domain block (D_{DCT}).
6. Divide the domain blocks into groups using fuzzy clustering method by iteratively calculating the cluster centre and membership functions.
7. Compute the variance of all range blocks. If the variance is less than the threshold value, then the range block is coded by mean and go to step 10. Else code the range block by transformation as defined in (2).
8. For every range block, calculate the distance between range block and centre of each cluster and cluster with smallest distance is selected.
9. Code the range block by transformation only in the appropriate cluster. Search for matching domain block by performing scaling and rotation within the selected cluster. Store the position and scaling parameter that gives the minimum matching error.

10. Repeat step 7 for all range blocks until the entire image is coded. For each range block, a header is attached to the fractal code representing the coding type, i.e., either by mean or by transformation. Compressed image consists of mean image and fractal codes of all range blocks.

5. Implementation Results

The images used for testing the proposed method are of size 256 × 256 gray scale images. The mean image size obtained from averaging the original image is of the size 64 × 64. The performance is compared using the parameters compression time, decompression time, compression ratio, PSNR (Peak Signal to Noise Ratio). The proposed fractal coding method is tested with the test images for range blocks of size 4 × 4 and step size 4. Here range and domain are assumed to be of same size. For deciding the uniformity of the range block, a threshold of 5 is assumed. The quality of the reconstructed image is evaluated by the PSNR value. The efficiency of proposed method considers the time taken for coding and the maintenance of PSNR value.

5.1. Results and Discussion

Standard gray scale images like Dune, Lena, Goldhill, Pepper, Parrot and Sailboat are used as input for testing. The simulation environment considered is Intel core i7 processor with processing speed 3.40 GHz and 2.00 GB RAM. The original image is shown in Figure 2-a. Figure 2-b shows the mean image and the classification of blocks to three clusters is shown in the Figure 2-c. The reconstructed image is shown in Figure 2-d. Figure 3 shows the original and reconstructed images using the proposed method. Proposed method is tested for various images and the performance parameters are listed in the Tables 1 and 2. Provides a comparison of compression by base iteration-free method and the proposed method.

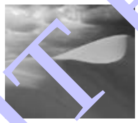

a) Original Lena image.


b) Mean image.


c) Classified blocks.


d) Reconstructed image.

Figure 2. Output images obtained using DCT.


a) Dune-original image.


b) Dune-reconstructed image.


c) Peppers-original image.


d) Peppers-reconstructed image.

Figure 3. Comparison of original and reconstructed images.

Table 1. Compression results for different images using proposed method.

Image	Compression Time(sec)	Decompression Time(sec)	PSNR(in dB)	Compression Ratio (%)
Lena	14.38	0.23	30.97	82.65
Parrots	11.54	0.22	30	84.59
Peppers	14.57	0.23	30.21	82.05
Mandril	17.69	0.25	23.54	79.46
Dune	7.35	0.25	38.59	88.07
Sailboat	14.31	0.23	28.94	82.58

Table 2. Test results for Fuzzy clustering using DCT method and iteration-free method.

Name of the Image	Compression ratio (%)	Compression Time (sec)		Compression Time Reduction Factor	PSNR		PSNR Reduction in (%)
	Iteration-Free and Proposed Fuzzy Clustering using DCT Method	Iteration-Free Method	Proposed Fuzzy Clustering using DCT Method		Iteration-Free Method	Proposed Fuzzy Clustering using DCT Method	
Lena	82.64	588.26	14.38	40.91	33.98	30.97	8.86
Parrots	84.59	478.27	11.54	41.44	32.81	30	8.56
Peppers	82.05	621.66	14.57	42.67	33.98	30.21	11.09
Mandril	79.46	767.40	17.69	43.38	25.65	23.54	8.23
Dune	88.07	282.31	7.35	38.41	45.12	38.59	14.47
Sailboat	82.58	609.81	14.31	42.61	30.08	28.94	3.79

From the observation of Table 2, it is seen that there is a drastic fall in the coding time by using iteration-free fractal coding method using fuzzy clustering on DCT coefficients than the base iteration-free method. It shows that there is large reduction in compression time, though the amount of reduction varies over the test images. The reduction of compression time is calculated as compression reduction time factor. The largest reduction of the compression time by the proposed method is 43.38 times less than the base iteration-free method. This drastic reduction in the compression occurs for the Mandril image. The smallest reduction of the compression time is 38.41 times less than the iteration-free method which occurs for the Dune image. On an average the reduction in compression time is about 41.59 times. Thus Fuzzy clustering using DCT coefficients method is very advantageous when the compression time reduction is considered.

6. Conclusions

The proposed fuzzy clustering based fractal coding is performed on DCT coefficients which reduces the computational complexity. Here the mean image is used for the construction of domain pool. Domain blocks are divided into three groups using fuzzy clustering method which speeds up the encoding process since the number of domain blocks to be searched is reduced. Further the decoding process is simplified by iteration-free decoding process. The proposed method is compared with the conventional non-iterative fractal coding method. Experimental results show that the proposed method has focused on achieving good reduction in compression time of about 42 times when compared to iteration-free method while at the same time reduction in PSNR is only about 9% thereby achieving good quality of the reconstructed images.

Figure 4. Shows the compression time for proposed and iteration-free method and the comparison of PSNR value is shown in Figure 5. There is only slight degradation in the quality of the reconstructed image.. The maximum reduction in quality is 14.47% which occurs for the Dune image. The minimum reduction in quality occurs for the Sailboat image amd is 3.79%. Average reduction in quality is 9.17%. This is an acceptable small value. When it is compared to the advantage of reduction in compression time, it does not make significant impact. Hence, the proposed fuzzy clustering clustering based FIC technique with step size four yields great reduction in compression time with only small reduction in quality when compared to the iteration-free method with search step size one.

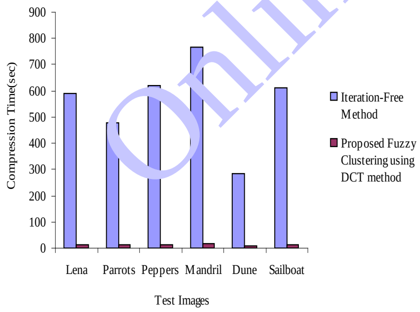


Figure 4. Compression time for proposed and iteration-free method.

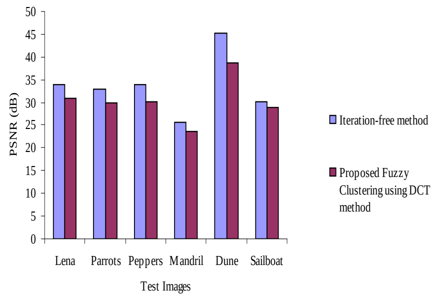


Figure 5. PSNR value for proposed and iteration-free method.

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