Australian Journal of Basic and Applied Sciences, 8(18) December 2014, Pages: 483-489

AENSI Journals

Australian Journal of Basic and Applied Sciences

ISSN:1991-8178

Journal home page: www.ajbasweb.com

Comparative Study on Fractal Image Compression

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ARTICLE INFO

Article history:
Received 19 August 2014
Received in revised form
19 September 2014
Accepted 29 November 2014
Available online 15 December 2014

Keywords:
Local Fractal Dimension, Fractal compression, Domain pool, Affine transformations, Pearson's Correlation Coefficient, Mean image

ABSTRACT

Conventional fractal image compression scheme requires a large amount of encoding time for performing range-domain mapping. One solution to this problem is to reduce the size of the domain pool and restrict the search space by classification or clustering methods. In this paper, Base Iteration-Free Method, Local Fractal Dimension and Pearson's Correlation Coefficient schemes are compared. First, Iteration process in the conventional fractal coding scheme requires larger memory size and high computation time. Iteration-free fractal coder is used to overcome this problem. The mean image of iteration-free process is considered as a domain pool for range domain mapping. The mean image is also stored along with the fractal codes. Second, Fractal Dimension (FD) is a measure to quantify how densely fractal occupies the space in which it lies. This characteristic has been used in texture classification, segmentation, clustering, edge detection and other problems. This measures the FD value of a local area rather than the whole image, the concept of LFD is applied in fractal image compression. Third, The Pearson Correlation Coefficient Method classifies the domain blocks into three classes according to the value. Only appropriate classified domain pool is required when matching blocks for a range block is searched. Experimental result shows that the Pearson Correlation Coefficient method gives better results and reduced the encoding time to about 43 times by combining the iteration-free techniques.

To Cite This Article: M. SOBIA and Dr.M.L.Valarmathi., Comparative Study on Fractal Image Compression. ***Aust. J. Basic & Appl. Sci.,*** *8(18): 483-489, 2014*

INTRODUCTION

Fractal image compression is a relatively new image compression method which uses similarities in different parts of the image. The concept of fractal coding was initially proposed by (Barnsley F, 1988) and extended by (Jacquin E, 1992) based on partitioned iterated function system (PIFS). In the conventional scheme, the image is partitioned into non overlapping range blocks and overlapping image blocks called domain blocks. Using contractive affine transformation (Arnaud E Jacquin, 1993), for each range block R, a domain block D that is similar to the range block is to be searched from the domain pool. The pure fractal-based schemes are not competitive with the current state of the art, but hybrid schemes incorporating fractal compression and alternative techniques achieve considerably greater success. Various methods have been suggested in review to extract the similarity information and to characterize this information as efficiently as possible in order to speed up the encoding process.

Review Of The Traditional Methods:

Most of the fractal-based encoding scheme does not achieve good results in encoding time. Several methods have been proposed to overcome this problem. The most common approach for reducing the computational complexity is the classification scheme. Many works have been conducted to improve the process of matching the domain block with range block in FIC (Wang Xing-Yuan *et al.,* 2011), (William Robson S, and HelioPedrini, 2011),(Jianji Wang *et al*., 2011), (Hsiu-Niang Chen *et al.*, 2010), (Yi-Ming Zhou *et al.*, 2009). In variance based accelerating (He C *et al.,* 2004) and region based fractal image compression schemes only selected part of the domain blocks are taken to reduce the searching time for a range block (Truong T. K *et al.*, 2004). To find the domain block that matches with the range block under consideration, exhaustive search of all the domain blocks of the image should be done. The classification or clustering methods make the encoding process faster by restricting the search space to only a subset of the domain block pool. To speed up the fractal encoder, a classification scheme based on the edge properties of image blocks is proposed in (Der-Jyh Duh *et*

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al., 2005). Kovacs (TamásKovács, 2008) classified domain blocks based on two parameters. The first parameter is the direction of the first approximate derivative and the second parameter is normalised root-mean-square (RMS) error of the fitting plane in the given block. (Xianwei Wu *et al*., 2005) and (Chong Sze Tong, and Minghong Pi, 2001) used standard deviation (STD) of domain blocks to classify them.

DCT coefficients are also used for fractal encoding enhancements. (Wohlberg B. E, and Gerhard De Jager, 1995) utilised DCT coefficients because the Root Mean Square distance is known to be sub-optimal. Instead of using the RMS distance, human visual system (HVS) weighting may be applied to DCT coefficients to provide more accurate measure of perceived distance. Another approach is to minimize the search by excluding domain blocks. Examples include Jacobs's method of skipping adjacent domain blocks (Jacobs E. 1992). In addition to the previous efforts, some 'no search methods' have also been proposed (ShenFurao, and Osamu Hasegawa, 2004) for fractal compression. (Xing-Yuan Wang, and Shu-Guo Wang, 2008) proposed a 'no search method' based on a modified grey-level transform with a fitting plane. The transformation reduces the minimum matching error between a given range block and its corresponding domain block, enhancing the possibility of successful domain-range matching. Some genetic algorithm methods were proposed to speed up encoding time (Wang Xing-Yuan et al., 2009). Most of the proposed FIC techniques are fast but the quality of the reconstructed image is not satisfactory.

Conventional Fractal Method:

In conventional fractal image coding technique (Gregory K. Wallace, 1992), the image is partitioned into a number of non-overlapping range blocks (Jacquin E, 1993). The larger domain blocks are selected from the same image and can overlap. The domain blocks D to the range block R using the contractive affine transformation. The grey scale image is transformed using the equation (1).

$$\hat{R} = i\{\alpha(S \circ D) + \Delta g\} \tag{1}$$

Where,

$\hat{R}$ Coded range block,

α Scaling factor, S Contractive transformation,

D Domain block,

Δg Luminance shift,

i Isometry

Then the fractal code describing the above contractive affine transform that has minimum matching error (MSE) between the original range block and coded range block is transmitted or stored.

Chang & Kuo Method Of Iteration-Free Coding:

In this method, the mean of all the range blocks are computed. A mean image is constructed from these mean values where each pixel of the mean image is the mean of the range block. A mean image of size M/B x M/B is constructed from the mean of the range block of the size B from the image of size M x M. The mean image is used as the domain pool (Hsuan T Chang, and Chung J. Kuo, 2000). In the mean image, the neighbouring blocks have high similarity since most parts of the blocks overlap. These overlapping produces redundancies between the domain blocks, hence, the coding performance will be improved compared with the conventional fractal schemes. The following contractive affine transformation is applied (Husan T Chang, and Chang J. Kuo, 2000).

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

The mean image is also transmitted along with the fractal code. To decode and obtain a particular range block of the image, the corresponding domain block from the mean image is taken and the corresponding contractive affine transformation is performed 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, thereby reconstructing the original image without any iteration. Because there is no iteration, the decoding time is drastically reduced.

Local Fractal Dimension:

When the search space is too large for exhaustive search domain pool reduction is an efficient way to reduce time. Fractal features have been widely used in object modeling and image classification. Since the fractal dimension is useful to qualify the complexity of details, the value of local fractal dimension is an important feature of edge areas where intensities varies violently. To extract local features of an image, the local fractal dimension (LFD) is given by calculating the FD value of a local area rather than the whole image. The LFD value reflects the complexity of local image areas. The LFD value is related to image edges. Thus the local fractal dimension (LFD) is to extract local fractal feature of gray-scale images thereby detecting edges (XiaodongZhuang, and QingchunMeng, 2003).

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Encoding Using LFD Clustering:

In the non- iterative fractal coding scheme the domain pool is pre-processed. The mean image formed from the original image is partitioned into block size m x m. The fractal dimension of these blocks called local fractal dimension is obtained by the differential box counting method with the modification said. These LFD values of the blocks help in clustering the domain pool. These LFD values are local feature of the image and describe the image complexity at those blocks. The FD can be computed using SSIM methods (Jianji Wang, 2011), here the LFD value of every block can be computed using the differential box counting method which takes very low computational time (Yi-Ming Zhou, 2009).

Initially a pre-processing analysis of the mean image is made by calculating the LFD of each domain block. The domain blocks with sharper edges will have higher fractal dimension whereas the smooth blocks will have lesser fractal dimension. Based on the LFD values the domain pool is grouped into the following three clusters. Let the Min represent the minimum of the LFD values, Max represent the maximum of the LFD values.

- Group the domain blocks having LFD values ranging from $\min \textit{ to } \min + \frac{1}{4}(\max - \min)$ as the first cluster.
- Then group the domain blocks having LFD values ranging from $\min + \frac{1}{4}(\max - \min) \textit{ to } \min + \frac{3}{4}(\max - \min)$ as the second cluster
- Then group the domain blocks having LFD values ranging from $\min + \frac{3}{4}(\max - \min) \textit{ to } \max$ as the third cluster.
- During the mapping process the LFD values of every range block is calculated. Based on the calculated value, search is made in any one of the three domain block clusters.

Algorithm for Encoding:

The LFD algorithm is summarized as follows.

1. Divide the image into non-overlapping blocks called range blocks and compute the mean image (domain pool).
2. Calculate the variance of each range block using equation (3)

$$Var\{R\} = \frac{1}{B^2} \sum_{0 \le i,j < B} (r_{i,j} - \mu_R)^2 \tag{3}$$

where$r_{i,j}$ denotes the $(i,j)^{th}$ pixel value of the range block R, and is the mean value of the range block.

3. Perform LFD Calculation on all the range and domain blocks of size 4 x 4.
4. Cluster the domain pool based on the LFD values.
5. If the variance of the range block is less than the threshold value, code the range block by the mean value, and go to step 8. Otherwise go to step 7.
6. Code by affine transformation by performing scaling and rotation on the respective cluster of domain pool based on the LFD of the range block.
7. Repeat step 6 for all range blocks.

Apcc Based Fractal Image Compression:

Conventional fractal image compression scheme requires a large amount of encoding time for performing range-domain mapping. It is reduced by classification of image parts based on Pearson's Correlation Coefficient (Jianji Wang, and Nanning Zheng, 2013). Using these methods, all the domain blocks are classified into three classes according to the Pearson's correlation coefficient classification method. Iterative decoding process is simplified by employing the iteration-free method. The Pearson correlation coefficient is a measure of the strength between the two linear association variables, denoted by r taking a range of values from +1 to -1.

APCC Computation:

The input image of size M x M is partitioned into the non-overlapping range blocks of size B x B, and compute the mean image which is used as the domain pool. Then Absolute Pearson's Correlation Coefficient (APCC) for all the range and domain blocks is calculated. The computational procedure for APCC is described below.Correlation coefficient is computed by substituting the estimated value of the covariance and variances of the range and domain blocks into the formula given below. Correlation coefficient r is defined as:

$$r = \frac{SS_{XY}}{\sqrt{(SS_{XX})(SS_{YY})}} \tag{4}$$

where

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$SS_{XX} = \sum (x_i - \bar{x})^2$ is the variance of the block R.

$SS_{YY} = \sum (y_i - \bar{y})^2$ is the variance of the block D.

$SS_{XY} = \sum (x_i - \bar{x})(y_i - \bar{y})$ is the covariance's between R and D.

Based on the values the domain pool is grouped into the following three clusters. Let min represent the minimum of the APCC values and max represent the maximum of the APCC values.

Group the domain blocks having APCC values ranging from min to min + ¼ (max-min) as the first cluster.

Group the domain blocks having APCC values ranging from min + ¼(max - min) to min + ¾ (max -min) as the second cluster. Group the domain blocks having APCC values ranging from min+3/4(max-min) to max as the third cluster.

During the mapping process, the APCC values of every range block are calculated. Based on this value, search is made in any one of the three domain block clusters. The total domain block number in the three domain classes is only one eighth of the domain block number in BFIC, which can greatly reduce the pair -wise comparisons between the range blocks and domain blocks. All the domain and range blocks are classified into 3 classes to reduce the pair wise comparisons further. More importantly, the reconstructed image quality is well preserved.

Algorithm for Encoding:

1. Partition the input image of size M x M into the non-overlapping range blocks of size B x B and compute the mean image which is used as the domain pool.
2. Compute APCC for all the range and domain blocks.
3. Cluster the domain pool based on the APCC values.
4. For each range block, check if the variance of the range block is less than the threshold value (here threshold value is chosen as 5), code the range block by the mean value, and go to step 6.
5. Find the cluster to which the range block belongs to, based upon its APCC value. Code the range block by transformation using scaling and rotation within the respective cluster of domain blocks to find the transformation parameters that gives minimum error between the transformed domain block and the range block.
6. Repeat step 4 for all range blocks. Attach a header to the fractal code of each range block. It represents the coding status of the range block, i.e. whether it has been coded by mean or by transformations. Then mean image and fractal codes are stored together as the representation of the compressed image.

Experimental Results And Analysis:

The proposed technique is tested on standard gray scale images of size 256 x 256 with 8 bit pixel values. The given image is partitioned into blocks of size 4 x 4. A threshold value is set to 5 for variance to decide whether to code the range block by mean or by affine transformation. The search is performed in domain pool to map best matching domain block with minimum distortion and classification method. A scaling parameter is selected in the set (n/4, n=1,2,3,4,5,6,7,8}.

Simulation Results:

LFD-based method and Pearson's correlation coefficient are used to compare the performance with different parameters, for seven standard images. Table 1 shows the comparison between the compression by iteration-free method, LFD method and Pearson's Correlation Coefficient for gray scale images. Compression time for the different images is given below. LFD and Pearson correlation coefficient shows a slight reduction in the quality of the image.

Table 2 shows that for any image the PSNR obtained is similar to the conventional iteration-free method. Figure 1 (a) shows the original image and Figure 1 (b) the reconstructed image. The test images outputs for the Pearson's Correlation Coefficient method obtained are shown in Figure 2 and the LFD-based technique yields much faster compression time than the conventional method, like Base Iteration-Free method there is huge reduction (43 times lesser) in the compression time as shown in table 1. Comparing both the methods Pearson's Correlation Coefficient is more efficient indicated by the parameters computed.

Figure 3 shows the compression time for the various images for Base Iteration-Free method, LFD method and Pearson's Correlation Coefficient method. Figure 4 shows the PSNR for the same set of images. Using these methods, there is a slight reduction in the quality of the image.

The above experiments have been carried out on Intel i7 CPU with 3.40 GHz preprocessing speed and with 2.00 GB RAM. Standard image like Goldhill, Sailboat, Dune, Lena, Parrots, Mandrill and Pepper is tested.

(a) Original Image (b) Reconstructed Image

Fig. 1: the original and reconstructed images using local fractal dimension method.

(a) Original Image (b) Mean Image (c) Classified Image

Fig. 2: Outputs for the Pearson's Correlation Coefficient Method.

Table 1: Comparison of Compression Time (in seconds).

Images	Base-Iteration Free Method	LFD based Method	Pearson's Correlation Coefficient method
Lena	587.80	25.39	13.57
Dune	281.67	20.92	6.56
Parrot	477.15	22.22	11.51
Mandrill	765.61	29.82	17.61
Pepper	620.28	26.98	14.52
Sailboat	591.19	30.95	13.93
Goldhil	725.90	34.58	16.77

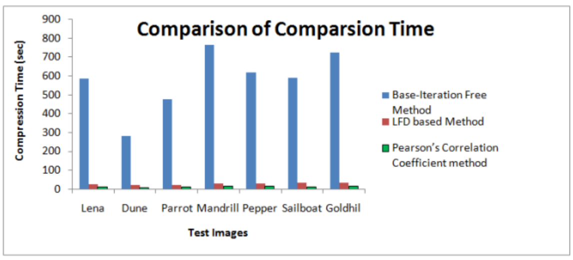

Fig. 3: Comparison of Compression Time.

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Table 2: Comparison of PSNR (in dB).

Images	Base-Iteration Free Method	LFD based Method	Pearson's Correlation Coefficient method
Lena	32.98	31.23	30.80
Dune	42.11	41.14	40.34
Parrot	31.89	30.65	30
Mandrill	24.95	23.29	23.61
Pepper	32.81	30.65	30.42
Sailboat	31.89	29.62	29.15
Goldhil	33.50	31.06	30.88

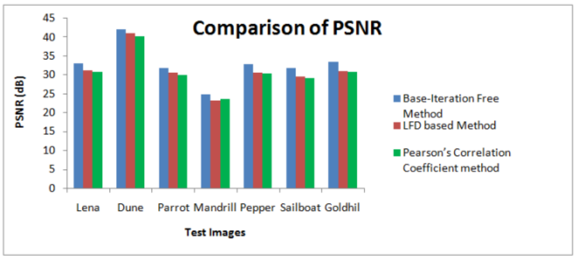

Fig. 4: Comparison of PSNR.

Conculsion:

One of the common drawbacks in using Fractal image compression is its larger encoding time.Many schemes have been proposed to speed up the encoding process. This paper has been compared with the Base Iteration-free method, Local Fractal Dimension and Pearson's Correlation Coefficient methods and an exhaustive simulation has also been performed for standard images like Lena, Dune, Parrot, Mandrill, Pepper and sailboat. Thus the compared simulation shows that the Pearson Correlation Coefficient method reduces the compression time by a factor of 43times while at the same time ensuring the same quality as that of conventional fractal image compression technique.

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