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Resemblance in Range Domain Block for Image Compression using Fractal Image Compression

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Abstract*—Fractals can be an effective approach for several properties like resolution independence, fast decoding, and very competitive rate-distortion curves. Our proposed method reduces the encoding time of an image by classifying the blocks according to an approximation error measure. It performs range and domain block comparisons with respect to a preset block, then we use Binary Search Tree as a data structure where we commit result and insertion and searching of an error is performed. Due to this it is possible to reduce drastically the amount of operations needed to encode each range.

***Keywords*— Fractal image com-pression, Classification, feature vector, approximation error, Range ,Domain.**

I. INTRODUCTION

The objective of image compression is to reduce lopsided and unwanted image data in order to be able to store and transmit data in an efficient form. The reduction in file size allow more images to be stored in a given quantity of disk or memory space, It also bring down the time required for images to be sent over the internet or download from web pages. The pros of lossy compression are that tremendous compression ratio may be obtained by ignoring aspects of the data that are trivial.

The most popular lossy compression approach [2] is based on fractal image compression (FIC) [3]. This technique capitalize on affine redundancy that is present in distinctive images in order to achieve high compression ratios, generally maintaining good image quality with resolution independence. The main downside of FIC however is that there is a very high computational cost associated with the encoding phase [4]. An assortment of methods for compressed image and every method has three basic steps transformation, quantization and encoding. Compression is achieved by the removal of one or more of the three basic data redundancies as Coding Redundancy, Interpixel Redundancy ,Psychovisual Redundancy.

Let n1 and n2 denote the number of information carrying units(usually bits) in the original and encoded images respectively, the compression that is achieved can be via the compression ratio, CR = n1 /n2.

In the last years, the interest of researchers has focused on a lossy compression technique based on fractal theory. In spite of the manifold advantages offered by fractal compression, such as high decompression speed, high bit rate and resolution independency, the greatest disadvantage is the high computational cost of the coding phase

Many different solutions have been proposed for this problem [1],[2],[5] for instance, modifying the partitioning process or providing new classification criteria or heuristic methods for the range and domain matching problem. All these approaches can be grouped in two classes: classification methods and feature vectors [6]. The paper is organized in following sections. Section1: gives a brief introduction; Section 2: overview on Fractal image compression; Section 3: will focus on proposed approach followed by conclusion and future scope.

II. BASIC TERMINOLOGY

A. Affine Transformation

An affine transformation maps a plane to itself. The general form of an Affine Transformation is

$$w_i\begin{pmatrix}x\\y\end{pmatrix}=\begin{pmatrix}a_i & b_i\\c_i & d_i\end{pmatrix}\begin{pmatrix}x\\y\end{pmatrix}+\begin{pmatrix}e_i\\f_i\end{pmatrix} \qquad (1)$$

Affine transformations can skew, stretch, rotate, scale and translate an input image.

B. Constractive Transformation

A transformation w is said to be contractive if for any two points P1, P2, the distance d(w(P1),w(P2)) < sd (P1,P2)for some s < 1, where d = distance. This formula says the application of a contractive map always brings points closer together.

C. The Constractive Mapping Fixed Point Theorem.

This theorem says something that is intuitively obvious: if a transformation is contractive then applied repeatedly starting with any initial point, we converge to a unique fixed point. If is a complete metric space and w:x→x is contractive, then W has a unique fixed point│w│.

D. Self Similarity

Subsets of fractals when magnified appear similar or identical to the original fractal and to other subsets. This property called self-similarity [7, 8] makes fractals independent of scale and scaling. Thus there is no characteristic size associated with a fractal.

Fractal image Compression is a lossy compression technique that has been developed in the early 1990s. fractal image compression is based on partition a given image into non overlapping blocks of size rxr, called range blocks and form a domain pool containing all of possible overlapped blocks of size 2rx2r, called domain blocks associated with 8 isometries from reflections and rotations [7]. For each range block, it exhaustively searches, the domain pool, for a best-matched domain block with the minimum rms error after applying a contractive affine transform to the domain block. The problems that occur in fractal encoding are the computational demands and the existence of best range-domain matches [9]. However searching the domain pool is highly computationally intensive. For an nxn image, the number of range blocks are (nxn/rxr) and the number of domain blocks are (n-2r+1) x (n-2r+1). The computation of best match between a range block and a domain block is O (r2). If r is constant, the computation complexity of entire search is O (n4).

In Jacquin's method the image is partitioned in sub images called as 'Range blocks' and PIFS are applied on sub-images, rather than the entire image [10]. Fractal compression system the first decision is to choose the type of image partition for the design of range blocks. A wide variety of partitions have been investigated but we have used quad tree partitioning. Our partition method is based on a split/merge approach as introduced by Horowitz and Pavlidis in [11]. Fig 1. shows the whole process of fractal image encoding. In any Fractal compression system the first image is partitioned to form of range blocks. Then domain blocks are selected. This choice depends on the type of partition scheme used. The domain pool in fractal encoding is similar to the codebook in vector quantization (VQ) referred as virtual codebook or domain codebook. Then set of transformation are selected which are applied on domain blocks to form range blocks and determines the convergence properties [2], [3] of decoding. The reconstruction process of the original image consists on the applications of the transformations describe in the fractal code book iteratively to some initial image, until the encoded image is retrieved back.

There are hundreds of applications of fractal from different aspects, such as generating computer aided mammography, creating realistic image, producing fractal music and etc. Fractal Image compression is a very advantageous technique in the field of image compression. The coding phase of this technique is very time consuming because of computational expenses of suitable domain search. In this project we have proposed an approximation error based speed-up technique with the use of feature extraction. Proposed method reduces the number of range-domain comparisons with significant amount and gives improved time performance.

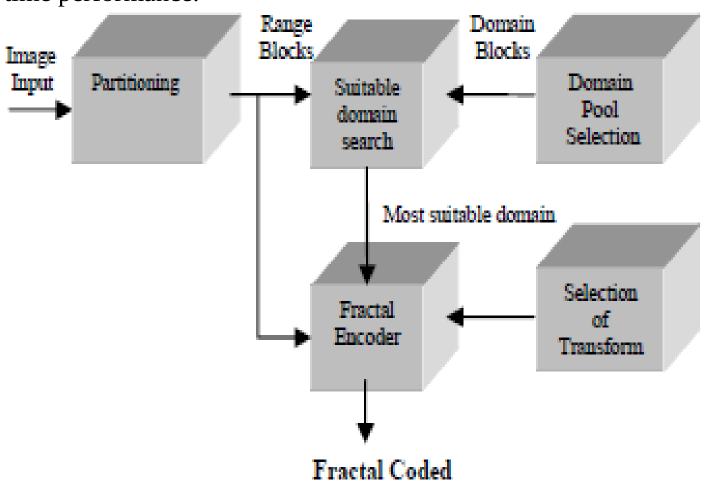

Fig. 1. Block diagram of fractal image encoding process.

III. PROPOSED APPROACH

The major disadvantage of fractal coding approach is the high computational effort of the encoding process compared for e.g. the JPEG algorithm. This is due to the costly "full search" of the transform parameters within a fractal codebook. Fractal-based algorithms are strongly asymmetric because, in spite of the linearity of the decoding phase, the coding process is much more time consuming. As many different solutions have been proposed for this problem, but there is not yet a standard for fractal coding. Therefore our proposed algorithm reduces the complexity of an image and increases speed of processing. The coding phase by classifying the blocks according to an approximation error measure. It is formally shown that postponing range and domain comparisons with respect to a preset block, it is possible to reduce the amount of operations required to encode each range blocks.

In the DRDC technique whole process of suitable domain search is based on approximation error. In the first step the image is partitioned in sub-images to form range blocks. Then in second step domain blocks are selected with the double size as that of range blocks. An average block given as $(\bar{d})$ is computed first, which is equal to the average of all range blocks (ri),

$$\bar{d} = \frac{1}{|R|}\sum_{r \in R} r$$

then a few number of features as mean, variance, skewness, kurtosis of image blocks are extracted and feature vector (*f* [*m, v, s, ku*]) for range, domain and average blocks are formed. Further operations of desired task are performed on these feature vectors. Then the range-domain comparisons are done in two parts. The domain and range feature vectors are compared. This is compared with feature vector of preset block which is a separately calculated block of image.

The calculated mean value of image gives the measure of average greylevel of image (m), standard deviation (v) defines the dispersion of its greylevel from mean value. Skewness (s) describes existence of symmetry and asymmetry from the normal distribution in images. Skewness can given as a form of negative skewness or positive skewness, depending on whether data points are skewed to the left (negative skew) or to the right (positive skew) of the data average. Kurtosis (ku) characterizes the relative properties as peakedness or flatness of a distribution compared to the normal distribution. Positive kurtosis indicates a relatively peaked distribution where as negative kurtosis indicates a relatively flat distribution of greylevels in the images.

In the algorithm the coding process is divided into two phases. In the first phase, domain feature vectors (*fdi*) are compared with feature vector of preset block ($f_{\bar{d}}$), in next step the difference between these vectors is computed. This difference which is equal to the Euclidian distance between the vectors and the approximation error. Later difference is computed and this set of error stored in a binary search tree, as shown in Fig. 2. A binary search tree is a specific case of a tree for storing data. First it is a binary tree, meaning that a node can at most have two children. A binary search tree, meaning that the child to the left of a parent is less than the parent, while the child on the right is greater than the parent. Operations can be performing such as insertion, search and nearest-neighbor search operations. In the second phase, considering range feature vector (*fri*) This range feature vector(*fri*) corresponding to the ith range block is compared with average feature vector ($f_{\bar{d}}$) and Euclidian distance between them is calculated. In next phase again error has been computed but it is not stored in the binary search tree. This error value is used as search key for nearest neighbor search for locating the best fitting domain for the given range. As shown in Fig. 3.

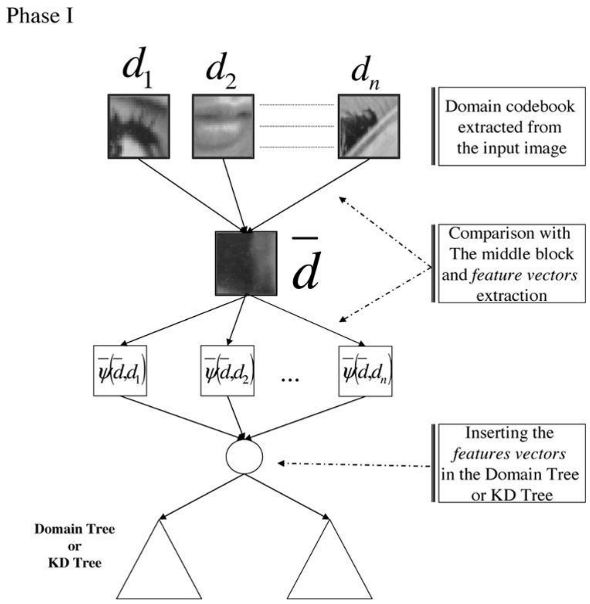

Fig. 2. First phase of DRDC technique

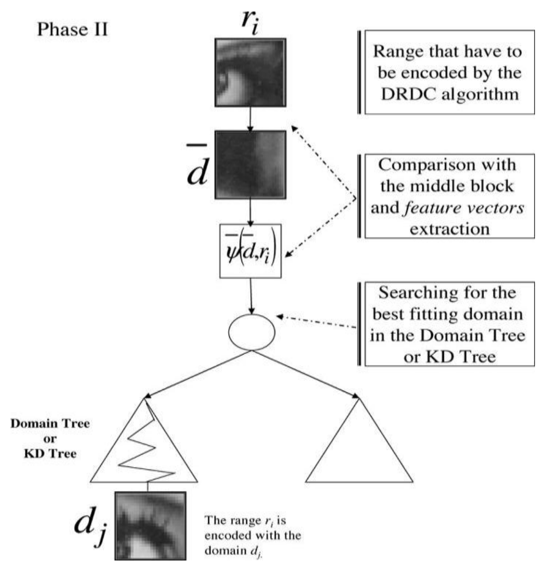

Fig. 3. Second phase of DRDC technique

Algorithm of DRDC technique by using error based approximation method.

Step 1: Compute the preset block ($\bar{d}$), equal to the average of all range blocks.

Step 2: Extract features (Mean (*m*), Standard deviation (*v*), Skewness (*s*), Kurtosis (*ku*) of domain, range and Preset blocks.

Step 3: Calculate Euclidian distance $\psi(f_{di}, f_{\bar{d}})$for all domain blocks.

$$\psi(f_{di}, f_{\bar{d}}) = \sqrt{(m_{\bar{d}} - m_{di})^2 + (v_{\bar{d}} - v_{di})^2 + (s_{\bar{d}} - s_{di})^2 + (ku_{\bar{d}} - ku_{di})^2}$$

Step 4: Store these error into binary search tree.

Step 5: Calculate Euclidian distance $\psi(f_{ri}, f_{\bar{d}})$

Given as $$\psi(f_{ri}, f_{\bar{d}}) = \sqrt{(m_{\bar{d}} - m_{ri})^2 + (v_{\bar{d}} - v_{ri})^2 + (s_{\bar{d}} - s_{ri})^2 + (ku_{\bar{d}} - ku_{ri})^2}$$

Step 6: Find the nearest value of these error by performing search operation on binary search tree.

Step 7: Assign domain block corresponding to the nearest error value in binary search tree to the desired range block.

By the above algorithm of DRDC which is considered as speed-up technique proposed in this paper. Which result in drastic reduction in time requirement of suitable domain search of images. In conventional method every range block is compared with all the domain blocks and approximation error between them is stored for each range block. Along with this search for least error is in done for every range block .Where as in this method, domain feature vectors are compared with average feature vector in domain code-book formation. And each range feature vector is compared once with average feature vector to form search key. We have saved the approximation error between average and domain feature vectors in binary search tree and the searching is done with deferent search keys in the same error space in binary search tree.

IV. Results

In conventional suitable domain search comparisons are to be done *RxD* times. Approximation error to be saved and minimum value is to be searched *R* times. In proposed method number of comparisons are reduces to *R+D*, approximation errors are saved only once and nearest value is searched *R* times. Comparisons are done on the basis of feature vectors rather than images so, it reduces complexity of computation.

To testify the efficiency of the proposed algorithm, we have chosen three standard images of Lena, Zelda and Goldhills respectively on four different parameter such as image size, encoding time, compression ratio and PSNR to do the experiments as shown in Table I. the original test image and reconstructed image has been shown in Fig 4-6.

Experimental parameters and demands are listed as follows:

1. Range Block size: 8×8.
2. Domain Block size: 16×16
3. Preset Block size: 8×8
4. Peak Signal-to-Noise Ratio (PSNR), which in decibels, can be computed as

$$\text{PSNR}=10 * log_{10}\left(\frac{M.N.255^2}{\sum_{m,n}(S_{m,n}-\bar{S}_{m,n})^2}\right)$$

Experimental Where M and N are image width and height, 255 is the maximum pixel value, $S_{m,n}$ is the pixel value in the original image and $\bar{S}_{m,n}$ is the corresponding pixel in the decoded image.

(a) Original image of Lena (256× 256× 8) (b) Decoded image of Lena (256× 256× 8)

Fig 4. Input image of Lena and decoding results of error based methods

(a) Original image of Zelda (b) Decoded image of Zelda

Fig 5. Input image of Zelda and decoding results of error based methods

(a) Original image of Goldhills

(b) Decoded image of Goldhills

Fig 6. Input image of Goldhills and decoding results of error based methods

TABLE I PERFORMANCE OF PROPOSED METHOD ON STANDARD IMAGE

Sr No.	Test Images	Image size	Encoding Time	Compression ratio	PSNR
1	Lena Image	998784	11.256187	32.0390	41.3095
2	Zelda	1210320	12.326582	31.7271	43.3091
3	Goldhills	1212960	24.834773	32.0380	39.0373

Comparison is performed with two different parameter such as encoding time and PSNR using standard method and proposed method as shown in Table II.

TABLE II PERFORMANCE COMPARISON BETWEEN PROPOSED METHOD ON STANDARD METHOD

Method	Test Image	Image Size	Encoding Time(s)	PSNR
Proposed method	Lena Image	998784	11.256187	48.3095
Standard	Lena Image	998784	55	21

V. CONCLUSIONS

The speed-up technique proposed here reported drastic reduction in time requirement of suitable domain search. we have adopted feature based classification method for fractal image compression called DRDC. It is based on an approximation error, which is computed deferring range/domain comparisons with respect to a preset block . The DRDC method based on an approximation error which uses binary search tree for performing insertion and searching of those error and shows results in terms of encoding time, compression ratio and PSNR. Due to binary search tree and error vectors that help us to reduce the computational cost of exhaustive search while still preserving a good image quality, less complexity with total time requirement of the desired process is reduced significantly.

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