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PROPOSED PYRAMID FRACTAL IMAGE COMPRESSION

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ABSTRACT

To evaluate the proposed pyramid fractal image compression, and comparing its result with traditional *FIC*, several tests were performed. A detailed investigation was carried out on the performance of the pyramid fractal image compression technique in order to view the performance of the last one in terms of encoding speed, compression ratio and reconstructed accuracy. We examine the performance of our new technique of fractal image compression based on pyramid partitioning domain step=2,$s_{quantize}$=5 and $o_{quantize} = 7$ using standard (256x256) gray-scale image. In new proposed pyramid technique reduce the encoding time to factor 5.7.No need to use the symmetry process in our new proposed pyramid technique, but we used in traditional technique to reach the best matching between range-domain block. The reconstructed image reaches the attractor at three iterations whereas the traditional technique need to eight iterations to reach the attractor.

INTRODUCTION

The theory of fractal image compression based on contraction –mapping theorem. Partition iterated function system (PIFS) is essentially a set of contraction mappings, is determined by analyzing the image. These mappings can exploit the redundancy that is commonly present in most images. This redundancy is related to the similarity of an image with itself, that is part A of a certain image is similar to another part B of the image, by doing an arbitrary number of contractive transformations that can bring A and B together (Chakrapani and SounderaRajan, 2008). These contractive transformations are actually common geometrical operation such as rotation, scaling, skewing and shifting. By applying the resulting PIFS on an initially blank image iteratively can be completely reconstructed an approximation to the original image at the decoder (Jacquin, 1992).
Fractal image encoding consists of:

- Partitioning an image into ranges block (*R*) and domains blocks (*D*).
- Search for an appropriate *D* block for each R block.
- Find an affine transformation that adjusts the intensity values in the *D* to those in the *R* (MadhuriA.Joshi, 2009).

After partitioning a given image into range *R* and domains *D*, blocks D_i and map sw_i should be found so that when w_i applied to the part of the image D_i, should be get something that is very close to the any part of the image R_i. From the overall, the encoding process implies finding the blocks R_i and corresponding D_i by minimizing distances between them, which is the goal of the problem (Fisher, 1994; Lai*et al*., 2002).

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Encoding Images

Encoding mechanism of fractal technique by using the partial self-similarity of the images as redundancy, self – similarity well approximating the block to be encoded is extracted from the image and the transform parameter for a contraction transform representing the self-similarity is used as code (Hannes Hartenstein and DietmarSaupe, 2000). The affine transformation is applied by using:

$$R = sD + o \qquad \text{... (1)}$$

Therefore, an image is partitioned into a set of range block(R_i). The encoding of each range block search through all of Domain Pool (D) to find a best domain D_i (i.e.D_i∈D) which minimizes the collage error:

$$E(R,D) = \frac{1}{n}\left[\sum_{i=1}^{n} r_i^2 + s\left(s\sum_{i=1}^{n} d_i^2 - 2\sum_{i=1}^{n} d_i r_i + 2o\sum_{i=1}^{n} d_i\right) + o\left(no - 2\sum_{i=1}^{n} r_i\right)\right] \qquad \text{... (2)}$$

Where n : the number of pixel in each block (i.e. block size H×W)

r_i : the range pixel value
d_i : the domain pixel value
s and o are also called the IFS coefficients, and determined by:

$$s = \frac{n(\sum_{i=1}^{n} d_i r_i) - (\sum_{i=1}^{n} d_i)(\sum_{i=1}^{n} r_i)}{n\sum_{i=1}^{n} {d_i}^2 - (\sum_{i=1}^{n} d_i)^2} \quad \dots\dots (3)$$

$$o = \frac{\sum_{i=1}^{n} r_i \sum_{i=1}^{n} {d_i}^2 - \sum_{i=1}^{n} d_i \sum_{i=1}^{n} d_i r_i}{n\sum_{i=1}^{n} {d_i}^2 - (\sum_{i=1}^{n} d_i)^2} \quad \dots\dots (4)$$

That is, find the part of image that most looks like the image above R_i. There are 8 ways to map one block onto another. Minimizing equation (2) means two things. First, it means finding a good choice for D_i, second, it means finding good contrast s_i and brightness o_i for w_i (Fisher, 1994; Mahadevaswamy, 2000)

The Proposed Pyramid Image Model

Pyramidal image models employ several copies of the same image at different resolutions. Let $f(x, y)$ be the original image of size$2^M x 2^M$. An image pyramid is a set of image arrays $f_k(x, y)$, k=0, 1,..., M, each having size $2^k x 2^k$. The pyramid is formed by low pass filtering and subsampling of the original image. The pixel $f_k(x, y)$ at level k of a mean pyramid is obtained from the average of its four neighbors $f_{k+1}(x', y')$ at level (k+1):

$$f_k(x,y) = \frac{1}{4}\sum_{r=0}^{1}\sum_{s=0}^{1}(2x+r, 2y+s) \quad \dots\dots.(5)$$

At the coarsest level (k=0), the image has size 1 and represents the average grey level of the original image. The finest level image $f_M$is the original image of size $2^M x 2^M$. As the number of the levels decreases, the image details are gradually suppressed and spurious low spatial frequency components are introduced due to the effect of aliasing. In fractal image compression we introduced a new appropriate criterion. The method significantly improved the encoding fidelity. The initial definition of the new metric is given in terms of the average local contrast of the block. We have the following inequality:

$$E = \frac{1}{N}\sum_{n=0}^{N-1}\left|I_n - \tilde{I}_n\right| \le \bar{I}T_B \quad \dots\dots\dots (6)$$

Where N is the block size, $I_n$is the original image, $\tilde{I}_n$is the fractal encoded image, $\bar{I}$ is the block mean and $T_B$is the contrast threshold. Now we can be represented $\tilde{I}_n$as an affine transform of the contracted domain blockI_{M-1} i.e. ,$s\check{I}_{M-1,n} + o$, where s is the contrast scaling factor and o is the brightness offset. The encoding error is measured in terms of weighted E norm. Thus, the encoding process needs to make the block matching under the criterion. In our work we design the encoding error threshold for each pyramidal level. The encoding error threshold at the finest pyramidal level will be the same as the in equation (6). The pyramidal search is first carried out on an initial coarse level of the pyramid. This initial search increases the encoding speed significantly, because not only the number of the domain blocks to be searched is reduced, but also the data within each domain block are only a fraction of those in the finest level. Then, only a few numbers of the fractal codes from the promising domain blocks in the coarse level are refined through the pyramid to the finest level with little effort. The proposed algorithm provides a gradual refinement of the fractal code. This process is repeated recursively until the finest level m is reached. The contracted domain block image I in the (M -1, n) in equation (6) is the corresponding block in $(M-1)^{th}$ level of the pyramid $f_{M-1}(x,y)$. When range blocks are of size$2^m x 2^m$, in equation (6) optimization objective function for the best matched domain block search can be rewritten as:

$$E = \frac{1}{4^m}\sum_{n=0}^{4^m-1}|D_n(s,o) - R_n| \quad \dots\dots\dots (7)$$

Where $D_n(s,o)$=$s\check{I}_{M-1,n} + o$is an affine of the scaled domain block and $R_n = I_n = f(x,y)$ is the range block to encode.
Note that for consistency with equation (6), we use a single subscript n as the index of the pixel at location (x, y), clearly$n = 2^m y + x$.
Therefore, equation (1) becomes:

$$R_n^k \cong sD_n^k + o \quad \dots\dots\dots\dots\dots\dots\dots (8)$$

From the original image a pyramid is created, the depth of which is computed by the range block size. Because the range block is defined in the image, the range block pyramid will be contained in the image pyramid with the k^{th}level of the range block pyramid corresponding to the $(M-m+k)^{th}$level of the image pyramid. Instead of a direct search of the minimum of the objective function at the finest level m.We propose a fast algorithm by introducing a smaller, approximate version of the problem at a coarser level k of the range block pyramid:

$$E = \sum_{n=0}^{4^k-1}|D_n^k(s^k,o^k) - R_n^k|, \qquad \text{for } k_\circ \le k \le m \quad \dots\dots\dots (9)$$

Therefore, at range block pyramid level k, the encoding amounts to finding the best matching domain block of size $2^k x 2^k$in the image of the size $2^{M-m+k} x 2^{M-m+k}$. For example, for an original image of size 256×256 (M=8) and range block size 16×16 (m=4), the search complexity at $k_\circ$=2 is that of image size 64×64 and range block of size 4×4. The k=$k_\circ$ level of the range block pyramid is said to be initial and every location of the image from the $(M-m+k)^{th}$ level of the image pyramid needs a test. A new feature of the algorithm is the need of the parameter (fractal code) optimization during the block matching. Table (1) shows the Pseudo-code targeting a pyramid encoding process

The Decoding Process of Proposed Pyramid Technique

We can summarize the decoding process by the following steps. Starting from any initial image, we repeatedly apply the W_i until we approximate the fixed point. This means that for each W_i, we find the domain D_i shrinks it to the size of its range R_i, multiply the pixel values by s_i and add o_i and put the resulting pixel values in position of R_i, Table (2) shows the pseudo-decoding algorithm

Table 1. Pseudo-code targeting a pyramid encoding process

1. Load an input image into buffer.
2. Partitioning the image into small blocks (SB) with non-overleap (i.e., range blocks).
3. Choose big blocks (BB) with overlap (i.e., domain blocks).
4. Gets first SB from R-block
5. Quantized s and o.
6. Perform all the affine transformations, by using equation (7).
7. Choose the block that resembles the R-block with the encoding error; compute the encoding parameters that satisfy the mapping. Those parameters represent one fractal elements.
8. Pack the parameters into a more compact shape in order to chive more compression.
9. Store the compact bit stream in the output.

Table 2. Illustrated Pseudo-Decoding process

1. Generate the first reconstructed domain image plane randomly, we may initialize the domain image with 0,1,2,…,128,..etc,values.
2. The values of the indices of (s_i) and (o_i) for each range block should then be mapped into the reconstructed values of (s_i) and (o_i) by using the de quantization process.
3. Each range block, in the image, is reconstructed by using equation (8), then located in its position in the decoded image plane (i.e., range pool).
4. Down sample the decoded (reconstructed) image (range pool) into the size of domain pool by averaging or integer sampling to produce a new domain pool.
5. Repeat step 3 until we reach the attractor state (i.e., decoded image will not be changed as we processed in the iteration).

The Proposed Pyramid Fractal Image Compression Results

The pyramid process methods we attempted to decrease encoding time while reducing error. In this method an image is highly compressed using the fractal scheme. The error is then affine transformed and compressed again. The second order error is again compressed and so on. Since the fractal scheme seeks self -similarity within the image, the error image should compress itself well, and this is true for the second order error as well, etc. Speed is gained since the compressions are high, requiring a small number of transformations and much fewer comparisons with traditional method.

The algorithm of the our proposed pyramid is implemented in the following steps;

1. Quad tree partition used for range blocks.
2. The initial range block size is 16×16.
3. The encoding error was determined for each range block.
4. Blocks which had an error exceeding the visual supra thresholds (when Gain Factor = 5 were split into four 8×8 blocks.
5. The initial level k_0 is set to 1.
6. The contractive factor s and grey level shift o are coded using 5 and 7 bit uniform quantizer.

The search step size h. When h=16, full search took approximately less than 144 seconds while pyramidal search took approximately less than 25 seconds.

Figure (1) is the result of the pyramidal search with different levels.

K=2	K=1
No.of blocks=1399	No.of blocks=3025
CR=10.12	CR=4.68
PSNR=32.33	PSNR=34.97
SNR=20.96	SNR=23.61
ET=13 sec	ET=19 sec

Figure 1. The reconstructed image at k=1, 2 values

Also, we studied the effect of variable value of m, k, and M which illustrated in equation (9). Table (3) show this effect if the range image fixed at 256x256 (i.e. M=8)

In decoding process to reconstructed image from three iterations only no need to more iteration because the attractor image reached. Figure (2) shows this process.

We get high values of PSNR of reconstructed image based on proposed pyramid technique. This effect can be seen in Table (4).

1-iteration

2-iteration

3-iteration

Figure 2. The reconstructed image used only three iterations to reach the attractor

Table 3. The different values of k applied on Naser image at M=8

K	m	Range Block Size	CR	SNR	PSNR	Encoding Time
1	1	256	2.74	26.2	33.4	25
1	2	128	3.03	23.9	31.1	24
1	3	64	4.21	23.03	30.4	23
1	4	32	6.10	22.5	29.7	22
1	5	16	7.28	21.4	28.7	21
2	2	256	5.71	29.8	35.1	23
2	3	128	6.32	17.9	34.4	21
2	4	64	9.10	16.84	32.9	20
2	5	32	9.64	18.6	34.9	19
2	6	16	11.44	17.3	29.5	17

Table 4. Showing the reconstructed image with high PSNR value

Iteration No.	PSNR	No. block	CR	SNR
1	22.20	3025	4.7	11.17
2	33.23	3025	4.7	21.86
3	34.97	3025	4.7	23.61

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