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Grouping the Range Blocks Depending on the Variance Coherence

Yun Jung Lee†, Young Bong Kim††

ABSTRACT

The general fractal image compression provides a high compression rate, but it requires a large encoding time. In order to overcome this disadvantage, many researchers have introduced various methods that reduce the total number of domain blocks considering their block similarities or control the number of searching domain block depending on its distribution. In this paper, we propose a method that can reduce the number of searching domain blocks employing the variance coherence of intensity values and also the number of range blocks requiring the domain block search through the classification of range blocks. This proposed method effectively reduces the encoding time and also a negligible drop of the quality as compared with the previous methods requiring the search of all range blocks.

Keywords: Fractal image compression, variance, classification

1. INTRODUCTION

Many researchers have accomplished great advances in the Multimedia techniques that include a variety of media contents such as audio, video, and so forth. In particular, image data compression and decompression techniques became one of main interest fields.

The fractal image coding has evolved greatly from its first version proposed by Jacquin.[1] Fractal image coding is based on the self-similarity that a rectangular area called a range block in an image shows very similar shape with another area called a domain block. Its main problem is to fastly generate the affine transformation converging between these two blocks in an image. The Fractal image coding has many advantages such as fast decoding, resolution independence, and high compression rate. While its drawback is to have a long computing time in encoding phase.

Since the Jacquin's algorithm is introduced, many researchers have developed several techniques that greatly speed up the fractal image coding.[2]

In some techniques, domain and range blocks are classified into some classes according to their common characteristics. The search of the best domain block for a particular range block is restricted within the same class.[3-6]

In addition to classification techniques, the nearest neighbor search techniques make an appropriate data structure presenting the feature vector and then select the candidates for searching from the data structure.[7-10]

Polvere and Nappi introduced two algorithms.[12] One is to combine two techniques proposed by Saupe[8] and Fisher[13]. The other algorithm is to consider the mass center to Saupe's algorithm. Lee and Ra tried to reduce the number of domain blocks searched in order to fine the best match for each range block using the current minimum distortion and variance difference between a candidate domain block and range block.[11]

※ Corresponding Author : Yun Jung Lee, Address : (608-737) 599-1, Daeyeon-3 Dong, Nam-Ku, Busan. Korea, TEL : +82-51-620-6396, FAX : +82-51-621-6396, E-mail : leeyj01@mail1.pknu.ac.kr

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† Dept. of Computer Science Graduate School Pukyung Nat'l Univ.

†† Dept. of Electronics, Computer and Telecommunication Engineering, Pukyong Nat'l Univ.
(E-mail : ybkim@mail.pknu.ac.kr)

These methods do not consider all domain blocks for a range block. So, it has become very important problem to select the adequate characteristics for rapidly deciding the most similar domain block for a range block.

In this paper, we propose an algorithm that select candidate domain blocks using the variance of each block in an image. It will speed up the encoding time because the search for a range block is restricted within candidate domain blocks with similar variances. We also try to restrict not only the number of searching domain blocks but also the number of range blocks requiring domain block search.

So, we first classify all of the range blocks into similar groups using the variance of each block, and then determine a key range block by means of comparing with the similarity of range blocks within same group. The domain blocks are searched only for the key range block of each group. From these results, we can deduce the fractal code for the remaining range blocks using the relationship between the key range block and the range block.

This paper is organized as follows: Section 2 describes existing fractal algorithm and the feature of variance. In section 3 we introduce our proposed method. Experimental results are given in section 4. Section 5 contains concluding remarks and future work.

2. GENERAL FRACTAL CODING

Fractal Image compression technique is based on the IFS(Iterated Function System) theory that can reconstruct the original image starting from arbitrary image. This method divides an image into range blocks of the same size. We search most similar domain block for a given range block in order to obtain transformation function between two blocks. The similarity between a range block and a domain block can be estimated by MSE (Mean Square Error). The MSE is defined as

$$MSE(R, D') = \frac{1}{n}\sum_{i=1}^{n}(s \cdot d_i + \sigma - r_i)^2 \qquad (1)$$

where D' is the result that an affine transformation is applied to a domain block. r_i and d_i represent pixel values of range block and affine transformed domain block respectively. s is a contrast scale coefficient and σ is a difference between the mean value of a range block and that of a domain block.

Average and variance of any domain block D can be calculated by

$$\begin{aligned} ave(D) &= \frac{1}{n}\sum_{i=1}^{n} d_i \\ var(D) &= \frac{1}{n}\sum_{i=1}^{n}(d_i - ave(D))^2 \end{aligned} \qquad (2)$$

For affine transformed block D', its average and variance expression are given as follows.

$$\begin{aligned} ave(D') &= s \cdot Ave(D) + \sigma \\ var(D') &= s^2 \cdot Var(D) \end{aligned} \qquad (3)$$

Therefore, we can express MSE between a range block and an affine transformed domain block such as follows.

$$\begin{aligned} &MSE(R, D') \\ &= \frac{1}{n}\sum_{i=1}^{n}(s \cdot d_i + ave(R) - s \cdot ave(D) - r_i)^2 \\ &= \frac{1}{n}\sum_{i=1}^{n}(s \cdot (d_i - ave(D)) - (r_i - ave(R)))^2 \end{aligned} \qquad (4)$$

As mentioned in the equation (4), we can see that the MSE between a range block and a transformed domain block is small when the difference between $s \cdot (d_i - ave(D))$ and $(r_i - ave(R))$ is small. In other words, it is quit probable that MSE between two blocks will depends on the difference of their variances. Our proposed algorithm is effected from this statistical features.

3. PROPOSED METHOD

3.1 Classification of Range Blocks

Fractal compression algorithm mostly spends many execution times in searching the most similar domain block corresponding to a range block. Therefore, the encoding time is very expensive because this algorithm has to examine a great number of domain blocks with respect to each range block every time. If the intensity values of two range blocks have similar variance, we can guess that two range blocks will have very similar group of searching domain blocks. Thus, we can use one of the two range blocks to obtain fractal code and then generate the fractal code of the other range block from its result. This idea can cut off the many execution times but it does not give a great effect on the quality of reconstruction image.

So, we first classify all range blocks into several groups using the block coherence and variance difference between range blocks.

In order to classify the range blocks, we first sort the range blocks in ascending order considering their variance. These range blocks will be grouped. As an initial state, we assume that each range block has its own group and becomes a key range block in the group. That is, the number of groups is equal to the number of range blocks.

Now, we examine the block coherence between each key range block with similar variance. If MSE between two key range blocks is lower than a given threshold, these range blocks are turned out to be the same shape and then merged into the same group. One of two range blocks becomes a new key range block of the merged group. This process will be iterated until we can not find range blocks to be merged. As a result, all range blocks are classified into several groups using variance and block coherence.

3.2 Searching Domain Blocks

We should greatly reduce the number of domain blocks to search for finding the most similar domain block of a range block. In order to restrict the number of searching domain blocks for a key range block, we will utilize the relationship between the variance and the MSE for each block as mentioned in chapter 2.

For this relationship, we first compute the variances for all of the key range blocks and all of the domain blocks and then sort the variance in ascending order.

Most previous works use the nearest likelihood searching technology to seek the domain block that looks most likely the feature of range block[6]. However, we examine the sorted domain blocks in order of variance to find a domain block whose variance presents small difference with a key range block. We also consider the order of the variances of key range blocks. We make a sorted range list and a sorted domain list that are composed of the variances of all the range blocks and all the domain blocks, respectively.

To find the most similar domain block to a key range block, we first choose candidate domain blocks to be compared with the key range block using variance. For the first key range block in the sorted range list, we compare the variance of the key range block with the domain blocks from the first domain block in the sorted domain list until find a domain block with the smallest difference in variance. If the domain block is found, we select some domain blocks near the selected domain block as candidate domain blocks.

And then we calculate the MSEs between the key range block and all of the candidate domain blocks. The remaining domain blocks are not considered. Fractal code is evaluated from an affine transformation between the domain block with the smallest MSE and the key range block.

As range blocks and domain blocks are sorted, the search for the next key range block is restarted from the previous selected domain block. This procedure is iterated up to the last key range block in sorted range list.

Thus, we obtained the fractal code for all key range blocks. From this fractal code, we can evaluate the fractal code for the other range blocks using the relationship between a range block and its corresponding key range block.

4. EXPERIMENTAL RESULTS

We have made the several experiments on a PC with an Intel Pentium Ⅳ 1.5GHz CPU and 256MB main memory. We have obtained the experimental results from a 256×256 gray scale image, as called "Lenna". The image is divided into non-overlapping 4×4 range blocks and overlapping 8×8 domain blocks. For each domain block, we considered eight isometric transformations. The performance of the our proposed algorithm is compared with the full search fractal coding algorithm and VPS algorithm proposed by Lee and Ra[11] for the encoding time and PSNR. We also consider all range blocks to show the efficiency of the range classification.

Fractal code bits for a range block include (x, y) position of the best match domain block(14bits), intensity offset(8bits) and isometric transformation (3bits). The compression method employs the same bits for the same sized range blocks. In our experiment, we employed the compression method with 1.54bpp.

As shown in Table 1, the encoding time of our method takes about 1.4% encoding time rather than that of full search and also is shorter than VPS.

Table 1. Results for the "Lenna" image

METHOD		NOD	Encoding Time		PSNR (dB)
			%	sec	
The method in [11]	Full Search	15,875	100	8,290	32.30
	VPS	3,775	25.4	2,109	32.30
Proposed Method	Full Search	15,625	100	2,106	32.97
	Method 1 (4096)	20	0.27	5.6	29.98
		200	1.34	28.21	31.33
		300	1.74	36.69	31.50
	Range Classification (2117)	20	0.33	7.0	29.91
		200	0.96	20.15	31.18
		300	1.32	27.17	31.39

*VPS : The proposed method in [11].
*Method 1 : the case that considers all range blocks(does not classify range blocks).
*NOD : the number of searched domain blocks per range block.

Method 1 is the result for considering all range blocks. When the number of searching domain blocks is restricted to 20, the encoding time takes 5.6 seconds, but the quality of reconstruction image comparing with the typical method is deteriorated from 32.97dB to 29.98dB. The encoding time for 200 and 300 candidate domain blocks took 28.21 seconds and 39.69 respectively. Their PSNRs in reconstruction image became 31.33dB and 31.50dB, respectively.

From these results, we can see that small number of candidate domain blocks does not give good results. That is, if we excessively reduce the number of candidate domain blocks such as the case of 20 in Table 1, the reconstruction image will face with the serious deterioration in quality. However, it is not good method to increase the number of candidate domain blocks to improve the quality in reconstruction image because of the encoding time.

In the case of Range Classification, when MSE threshold is 150 and 100 range blocks with similar variance are considered, all range blocks are classified into 2117 groups. The number of range groups are dependent on threshold value. In this case, when the number of searching domain blocks is restricted to 300, we obtain about 30% reduction in encoding time and also slight changes in the quality of reconstruction image. As shown in Fig. 1, original image is very similar with the reconstruction image of the proposed method.

(a) The original image (b) The reconstruction image

Fig. 1. The result image of "Lenna".

5. CONCLUDING REMARKS AND FUTURE WORK

In this work, we introduced a method that restricts the number of searching domain blocks using the variance coherence of the range blocks and the domain blocks.

To speed up the encoding time, we classified all of the range blocks into several groups that have the similar distribution of variance. And all blocks in the same group have the MSE of the block within a given threshold. We chose a key range block in each group and tried to obtain a fractal code only for the key range block. Their results are used in deducing the fractal code of remaining range blocks in corresponding group. Through the classification of range blocks using block coherence, we can make a greate speed-up in compression keeping similar quality of reconstruction image.

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Yun Jung Lee

She received her BS degree in computer science and her MS degree in computer and information from Pukyong National University, Busan, in 1995 and 1999. She is currently a PhD student in computer science department at Pukyong National University. Her research interests include computer graphics and Image compression.

Young Bong Kim

He received his BS degree in computer science and statistics from Seoul National University, Seoul, in 1987. He received the MS and PhD degrees in computer science from KAIST in 1989 and 1994, respectively. He is currently an associative professor in the department of electronics, computer and telecommunication Engineering at Pukyong National University. His current research interests are game programming, computer animation, and 3D object.