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Another Application of Fisher's Scheme

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Abstract

Fractal Image Compression (FIC) is one of the effective techniques for compression of natural and still images. In FIC method an image is partitioned into non-overlapping-range blocks and overlapping domain blocks. All the domain blocks are collectively called as domain pool. Size of the domain pool determines the complexity of the encoding phase. Each range block is encoded based on an affine similarity between the domain blocks. However FIC brings advantages of high compression ratio while preserving the resolution in the decompressed image, it lacks from its expensive computational cost due to the large searching space in the domain pool. In the previous method, block classification method was used to classify the domain pool and preset block is used to select the appropriate domain block. Since the domain pool was not accurately classified, certain complexity occurs in this method. To overcome this limitation we utilize two methods to reduce the computational complexity of the FIC. Initially the domain pool is classified into three classes based on Fisher's classification technique and then a Fast Fractal Image Compression (FFIC) is implemented to reduce the searching space in the classified domain pool.

Keywords: Fractal Image Compression (FIC); Range blocks; Domain blocks; Fisher's classification scheme; Fast Fractal Image Compression (FFIC)

Introduction

With the increasing demand for delivering still images, video sequences and animations, data compression remains an essential tool to reduce the cost of data transmission and storage times. Demands for the communication of multimedia data through the telecommunication network and accessing the multimedia data through the internet is growing explosively. The basic objective of image compression is to find an image representation in which the pixels are less correlated. The two fundamental principles used in an image compression method are redundancy and irrelevancy. Redundancy removes less useful information from the signal source and irrelevancy omits pixel values which are not noticeable by human eye.

The image compression techniques are mainly classified into two categories; Lossless techniques and Lossy techniques. In lossless compression techniques, the reconstructed image after the compression is numerically identical to the original image. Lossless compression can only achieve a modest amount of compression, and is preferred for archival purposes and often medical imaging, technical drawings, clip art or comics. Lossy methods are however especially suitable for natural images such as photos in applications where minor loss of fidelity is acceptable to achieve a substantial reduction in storage size. An image reconstructed from the lossy compression contains degradation relative to the original image.

However, lossy schemes are capable of achieving a high compression ratio, they produce imperceptible differences that can be called visually lossless [1]. Applications of these compression techniques include Joint Photographic Experts Group (JPEG), Discrete Cosine Transform (DCT) and Wavelet Transform (WT). JPEG is primarily a lossy compression method [2] and it is capable of producing high-quality compressed images. JPEG was designed specifically to discard information that the human eye cannot easily see. In DCT, an image is partitioned into blocks containing different frequencies where less important frequencies are discarded through quantization and more important frequencies are used to retrieve the image during the decompression process. The main advantage of DCT is minimization of blocking artefact. Wavelet based coding provides satisfactory image quality with a high compression ratio mainly due to a better energy compaction property of wavelet transforms. However, selecting a particular wavelet for a specific application is very tedious process [3].

Fractal Image Compression (FIC) is one of the lossy compression techniques. This technique provides high compression ratio and high quality reconstructed image with the advantage of very fast decompression process. Multiresolution property is another advantage of FIC. Hence, an image can be decoded at different resolutions. But, the long computation time in searching the domain pool during encoding step still remains the main drawback of FIC [4,5]. Several methods have been proposed to overcome this problem. The block classification scheme is the most common approach for reducing the computational complexity in fractal compression methods [6,7]. In such classification scheme, domain blocks are grouped. Another effective method is Fisher's classification that we use it in this study along with FFIC.

Methodology

In Fractal Image Compression (FIC) scheme, the input image is partitioned into two types of blocks: Range blocks, and Domain blocks. Range blocks are non-overlapping blocks of size $n \times n$, that the input image is partitioned into [8]. The pool consisting of these blocks is called range pool. The range blocks in the range pool are the blocks to be encoded. Domain block, on the other hand, are overlapping blocks of size $2n \times 2n$ that the input image is partitioned into. The

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pool consisting of these blocks is called domain pool. The blocks in the domain pool are contracted to the same size as the range blocks. In FIC, the domain pool is considered as a virtual codebook. The size of the domain pool is directly proportional to the complexity of encoding process because the larger the domain pool, the longer the search time [9,10].

In the encoding phase of the fractal compression, each range block is encoded by finding the best matched domain block within the domain pool. An image with the size of N × N is partitioned into a non-overlapping range blocks R_i, $\{R_1, R_2,..R_p\}$ of a predefined size, $n \times n$. Then, a search codebook called domain pool Ω is created from the image by taking all the domain blocks D_j, $\{D_1, D_2,..D_q\}$ of size $2n \times 2n$. The range-domain matching process is begun which consists of a shrinking of a domain block by averaging its pixel intensities, forming a block of size $n \times n$. For a given range block R_i, the encoder must search the domain pool Ω for the best matched domain block (see the equation (1)) [13].

$$R = s.D + o.1 \qquad (1)$$

Where s is a scale factor and o is an offset. Both s and o are scalar variables. Of note that, the encoding time can be reduced by reducing the size of the domain pool [14].

Because of all comparisons between range and domain blocks, the matching process is responsible for the exhaustive search time. In order to shorten the search time, two solutions could be envisaged. Firstly Fisher's block classification scheme is applied to classify blocks into a number of classes according to their common characteristics. Fisher scheme is an efficient classification technique proposed by Fisher [11]. In this method, a square block is subdivided into upper left, upper right, lower left and lower right quadrants, numbered sequentially. In each quadrant, the average pixel intensities and the corresponding variances are computed. It is always possible to orient (rotate and flip) the block in such a way that the average intensities are ordered in one of the following three ways (see the equation (2,3,4)):

$$a1 \geq a2 \geq a3 \geq a4 \qquad (2)$$

$$a1 \geq a2 \geq a4 \geq a3 \qquad (3)$$

$$a1 \geq a4 \geq a2 \geq a3 \qquad (4)$$

In the coding phase, only the range and domain blocks belonging to the same class are compared. Moreover, from the isometry operations that bring range and domain blocks in their respective major classes, it is possible to guess the isometry which maps the domain blocks in the range blocks and this avoids a complete search of the isometry set. According to the literature, this will speed-up the algorithm by the factor of eight [12].

Then, a Fast Fractal Image Compression (FFIC) procedure is used where only a few of the neighbouring blocks are considered for comparison [15,16]. Thus the size of the domain pool is reduced efficiently. For instance, the eight nearest neighbouring blocks is considered for search. If the given block possesses a horizontal edge, its left and right neighbours also possess similar horizontal edges, but not the other six neighbours. Similarly, if the block possesses a diagonal edge, then its left-up and right-down neighbours only possess a diagonal edge. Based on this property, the search space is confined and the compression speed is improved.

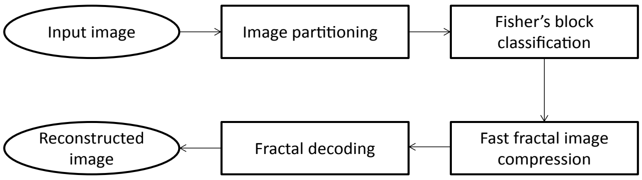

Figure 1: Block diagram of the compression scheme.

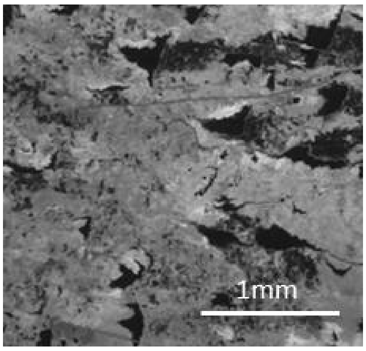

Figure 2: Agricultural image of Kaveripakkam.

The decoding procedure is performed iteratively. In the first iteration the decoded image is generated by implementing the contractive transformation derived from the fractal code on an arbitrary initial image. The result image is used as the starting point for the next iteration with the same contractive transformation parameters [17]. After a predefined number of iterations, the decoded image is converged to be most similar to the given encoded image (see the equation (5,6)).

$$T: R -> R$$

$$Tx = s.\ D + o\ 1 \qquad (5)$$

Equation (5) can be simply written as:

$$X = tx \qquad (6)$$

After several iterations, the resultant image converges to an image that approximates the original one [18,19].

The following block diagram provides a detailed explanation about this method.

The block diagram of the compression scheme is shown in Figure 1.

Results and Discussion

Fractal imaging of agricultural images

The input test image is a multispectral agricultural image of Kaveripakkam near Kancheepuram, Tamilnadu, India. The latitude and longitude of Kaveripakkam is 12.90545120 and 79.46195060, respectively. The spectral band 1 to 4 are used for compression in this work. Figure 2 shows the image which is a single band image with the size of 256 ×256 pixels.

In this work, the size of each range block is 32×32 pixels. There are 64 range blocks in the range pool Figure 3.

The size of the domain block is 64 × 64 pixels, generating 49

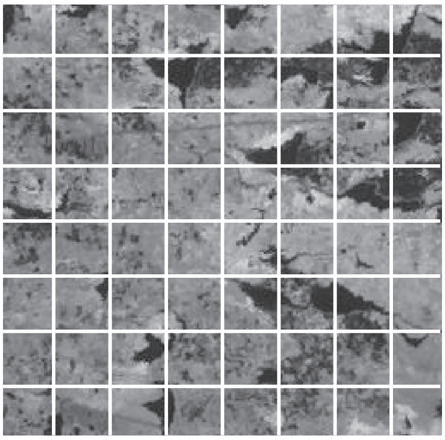

Figure 3: Non-overlapping range blocks with the size of 32 × 32 pixels.

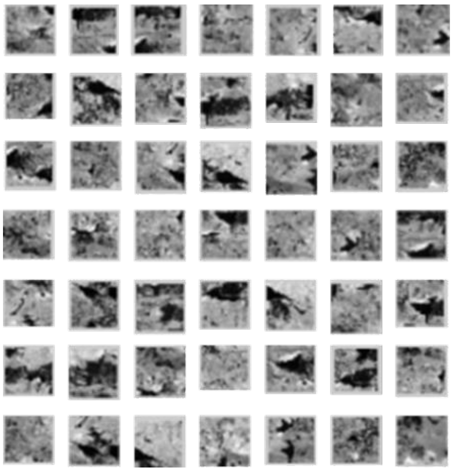

Figure 4: Domain blocks with the size of 64 × 64 pixels.

domain blocks in total Figure 4. The blocks in the domain pool are contracted to the same size as the size of the range blocks (i.e. 32 × 32). Size of the domain pool is directly proportional to the complexity of the encoding process; the larger the domain pool is, the longer the search time.

Fisher's classification methods

Partitioned image blocks (i.e domain blocks) are classified into three classes based on a statistical parameter, mean value. The blocks with their corresponding mean values are shown in Figure 5.

Fractal decoding

Fractal decoding follows a straightforward iteration procedure. In the first iteration the decoded image is generated by implementing the contractive transformation derived from the fractal code on an arbitrary initial image. After a certain number of iterations, the decoded image is converged (Figure 6(b)); the original image is shown in Figure 6(a), for comparison. The convergence of the iterated sequence starting with an arbitrary image is theoretically guaranteed by the fixed-point theorem [20,21]. The quality of the reconstructed image is analyzed using parameters such as Mean Square Error (MSE) and Peak Signal To Noise Ratio (PSNR) given in equations (7) (8), respectively. For a better quality image the PSNR value should be

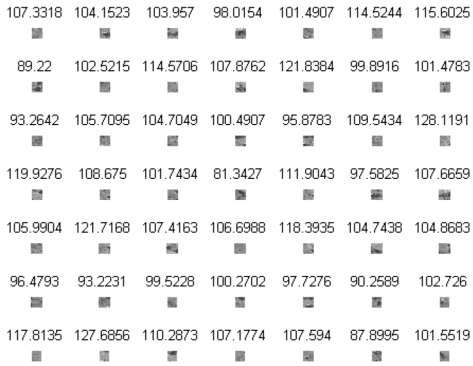

Figure 5: Code book containing all domain blocks with their corresponding mean values.

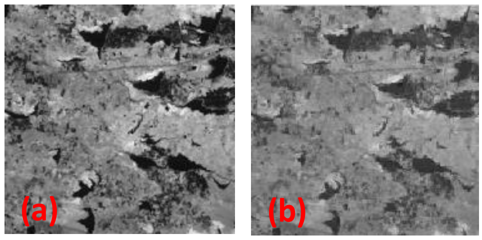

Figure 6: (a) Original agricultural image of Kaveripakkam (b) Reconstructed image after 10 iterations.

Table 1: Encoding time, decoding time, PSNR and MSE using FFIC method.

Images	Compression ratio	Encoding time (s)	Decoding time (s)	PSNR(dB)	MSE
Band 1	41.1	56.266	12.7970	39.6928	6.9791
Band 2	38.3	55.8440	12.9220	42.1071	4.0029
Band 3	42.1	57.5940	12.9210	37.1371	12.5710
Band 4	44.7	55.8750	12.8440	34.4768	23.1951
Lena	36.2	56.8750	13.0470	32.2677	38.5754

Table 2: Comparative results of MSE and PSNR of DCT method.

Images	Compression ratio	MSE	PSNR(dB)
Band 1	27.7	10.02	38.12
Band 2	23.6	7.27	39.52
Band 3	26.2	12.12	37.29
Band 4	29.3	13.83	36.72
Lena	25.7	15.41	36.25

higher and the MSE value should be lower.

$$MSE = \sum ((\sum squared\ error\ image)|(rows * columns)) \quad (7)$$

$$PSNR = * log10\ (255\hat{}2|MSE) \quad (8)$$

We performed this procedure for several images; the results are shown in Table 1. The results of the MSE and PSNR of the DCT method are also presented in Table 2 for comparison.

Comparing the results from Table 1 and 2, the increase of PSNR value in FFIC compared to those in DCT is obvious. For instance the PSNR of band 2 image from both tables is 42.10 dB in FFIC with its MSE being 4 dB, whereas in DCT method PSNR and MSE are 39.52

dB and 7.27 dB, respectively. The reasons for the improvements are as follows. Fisher's scheme uses a classification based on the mean values of the blocks. Moreover, here the number of domain blocks within a particular class is reduced which consequently reduces the encoding time.

Conclusion and Future Scope

The computational complexity of the fractal image compression is one main drawback in this method. Although there are several techniques available to speed up the encoding process, they make the system more complex, producing worse quality reconstructed images. A new FIC method based on the Fisher's scheme is implemented in this paper. In the Fisher's classification method, the blocks in the domain pool is classified into three classes. Hence the search space to get the best matched domain block from the domain pool for each range block is reduced. Experiment results show that the encoding time is reduced without affecting the quality of the reconstructed images.

This work can be extended by using it for compressing colour and hyper spectral images. In the studied method the range blocks are not overlapped. These blocks can be overlapped in the future studies to achieve an even higher quality reconstructed images. The same method with some modifications can be used in an optical imaging system for optimization as well as compression of its images [22-31].

References

1. Mekhalfa F, Avanaki M, Berkani D. A Losseless hybrid wavelet-fractal compression for welding radiographic images. Journal of X-ray science and technology. 2016: 1-3.
2. Avanaki MRN. Ebrahimpour: In-service video quality measurements in optical fibre links based on artificial neural network, Neural Network World journal. 2007; 17: 457-468.
3. Avanaki MRN, Laissue PP, Gh Podoleanu A, Aber A, Hojjatoleslami SA. "Evaluation of wavelet mother functions for speckle noise suppression in OCT images." Int. J. Graphics Bioinfo. Med. Eng 11. 2011: 1-5.
4. Barnsley MF, Jacquin AE. "Application of recurrent iterated function systems to images," Proc. SPIE. 1988; 1001: 122-131.
5. Truong TK, Kung CM, Jeng JH, Hsieh ML. "Fast fractal image compression using spatial correlation," Chaos Solitons Fractals. 2004; 22: 1071-1076.
6. He C, Yang S, Huang X. "Variance-based accelerating scheme for fractal image encoding." Electron. Lett. 2004; 40: 1052-1053.
7. Polvere M, Nappi N. "Speed-up in fractal image coding: comparison of methods," IEEE Trans. Image Process. 2000; 9: 1002-1008.
8. Distasi R, Nappi M, D Riccio D. "A range/domain approximation error-based approach for fractal image compression." IEEE Trans. Image Process. 2006; 15: 89-97.
9. He C, Yang SX, Huang X. "Progressive decoding method for fractal image compression". IEEE Proceedings in Visual Image Signal Processing. 2004; 151: 207-213.
10. Schwartz WR, Pedrini H. "Improved fractal image compression based on robust feature descriptors." Int. J. Image Graph. 2011; 11: 571-558.
11. Fisher Y. Fractal Image Compression-Theory and Application. New York: Springer-Verlag. 1994.
12. Wang J, Zheng N. "A Novel Fractal Image Compression Scheme with Block Classification and Sorting Based on Pearson's Correlation Coefficient", IEEE transactions on image processing. 2013; 22.
13. Tang X, Qu C. "Facial image recognition based on fractal image encoding." Bell Labs Tech. J. 2010; 15: 209-214.
14. He C, Xu X, Li G. "Improvement of fast algorithm based on correlation coefficients for fractal image encoding." Comput. Simul. 2005; 12: 60-63.
15. Kovacs T. "A fast classification based method for fractal image encoding." Image and Vision Computing. 2008; 26: 1129-1136.
16. Wang X, Wang Y, Yun J. "An improved fast fractal image compression using spatial texture correlation." Chin. Phys. B. 2011; 20.
17. Lasfar A, Mouline S, Aboutajdine D, Cherifi H. "Content-based retrieval in fractal coded image database," in Proc. 15th Int. Conf. Pattern Recognition. 2000; 1: 1031-1034.
18. Avanaki MRN, Ahmadinejad H, Ebrahimpour R.. Evaluation of Pure Fractal and Wavelet Fractal Compression Techniques. ICGST-GVIP Journal. 2009; 9: 41-47.
19. Avanaki MRN, Aber A, Ebrahimpour R. "Compression of cDNA Microarray Images based on pure-fractal and wavelet- fractal techniques". ICGST-GVIP Journal. 2011; 11: 43-52.
20. Avanaki MRN, Xia J, Wan H, Bauer AQ, Culver JP, Wang LV. High-resolution photoacoustic tomography of resting-state functional connectivity in the mouse brain. Proceedings of the National Academy of Sciences. 2014; 111: 21-26.
21. Yan-min He, Hou-jun Wang. "Fractal Image Decoding Based On Extended Fixed- point Theorem", Proceedings of the Fifth International Conference on Machine Learning and Cybernetics, Dalian. 2006; 13-16.
22. Avanaki MRN, Long Y, Paun MA, Hojjatoleslami SA, Podoleanu AG. Fast algorithm for blind optimization of optical systems. Statistics and methodology. Journal of Optoelectronics and Advanced Materials. 14(EPFL-ARTICLE-185748). 2012; 976-982.
23. Avanaki MR, Hojjat A, Podoleanu AG. Investigation of computer-based skin cancer detection using optical coherence tomography. Journal of Modern Optics. 2009; 56: 1536-1544.
24. Avanaki MR, Hojjatoleslami SA, Ebrahimpour R, Sarmadi H, Podoleanu AG. Genetic algorithm for optimization of optical systems. In Electrical Engineering (ICEE). 2010, 18th Iranian Conference on. 2010; 172-176.
25. Avanaki MR, Podoleanu AG, Price MC, Corr SA, Khoshki RM, Hojjatoleslami SA. Phantoms for performance assessment of optical coherence tomography systems. In SPIE BiOS. International Society for Optics and Photonics. 2012; 82290-82290.
26. Nasiri-Avanaki MRN, Aber A, Hojjatoleslami SA, Sira M, Schofield J, Jones C, et al. Dynamic focus optical coherence tomography: feasibility for improved basal cell carcinoma investigation. In SPIE BiOS International Society for Optics and Photonics. 2012; 82252-82252.
27. Nasiri-Avanaki MR, Sira M, Aber A, Hojjatoleslami SA, Schofield JB, Jones C, et al. Improved imaging of basal cell carcinoma using dynamic focus optical coherence tomography. In journal of investigative dermatology. 75 varick st, 9th flr, new york, ny 10013-1917 usa: nature publishing group. 2011; 131: 38-38.
28. Nasiri-Avanaki MR., Hojjatoleslami S, Paun H, Tuohy S, Meadway A, Dobre G, Podoleanu A. Optical coherence tomography system optimization using simulated annealing algorithm. Proceedings of Mathematical Methods and Applied Computing. WSEAS. 2009; 669-674.
29. Nasiri-Avanaki MR, Meadway A, Bradu A, Khoshki RM, Hojjatoleslami A, Podoleanu AG. Anti-spoof reliable biometry of fingerprints using en-face optical coherence tomography. Optics and Photonics Journal. 2011; 1: 91.
30. Hariri A, Bely N, Chen C, Nasiriavanaki M. Towards ultrahigh resting-state functional connectivity in the mouse brain using photoacoustic microscopy. In SPIE BiOS. International Society for Optics and Photonics. 2016. 97085-97085.
31. Nasiriavanaki M, Xia J, Wan H, Bauer AQ, Culver JP, Wang LV. High-resolution photoacoustic tomography of resting-state functional connectivity in the mouse brain. Proceedings of the National Academy of Sciences. 2014; 111: 21-26.