

# A New Time Reduction Encoding Scheme for Contourlet based Fractal Image Compression

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**Abstract**—A Image Compression algorithm based on Fractals in Contourlet domain is presented. Fractal Image Compression finds the self-similarity property of an image using Partitioned Iterative Function System (PIFS) to encode it. The major problem of FIC is poor image quality in high compression ratio and requires more computation time. In this paper, a new FIC scheme is proposed to improve the image quality at higher compression ratio and speed up the compression algorithm using Contourlet algorithm along with Genetic algorithm. This proposed algorithm compares the parameters BPP, CR, processing time and PSNR.

**Index Terms**— FIC, Contourlet transform, Genetic algorithm, Iterative Function System.

## 1 INTRODUCTION

The theory of image coding using iterative function system (IFS) was first proposed by Barnsley[1]. He modelled images by means of fractal objects, evolved through iterations of a set of contractive affine transformations. Iterated function system, along with collage theorem, helped Barnsley to lay foundation for the fractal-based image compression. A iterative function system (IFS) approximates a real image, to the relevant parameters of the transformations reducing memory requirements. The problem of fractal-based image compression is in finding appropriate parameter values of transformations whose attractor is an approximation of the given image. A fully automated fractal-based image compression technique of digital monochrome image was first proposed by Jacquin [2]. The encoding process consists of approximating the small image blocks, called range blocks, from the larger blocks, called domain blocks, of the image, through some operations. During the encoding process, for each range block separate transformations are obtained. The scheme also uses the theory of vector quantization [3] to classify the blocks. These set of transformations, when iterated on any initial image, will give a fixed point (attractor) that approximates the target image. This scheme can be viewed as partitioned iterative function system (PIFS). One such scheme, using PIFS, to store fewer number of bits (or to increase the compression ratio) was proposed by Fisher *et al.* [4].

Genetic algorithms with elitist model are used in finding the appropriate domain block as well as the appropriate transformation for each range block. GA's are adaptive search processes based on the notion of selection mechanism of natural genetic system [5]. GA's help to find the global near optimal solution without getting stuck at local optima as they deal with multiple points (spread all over the search space) simultaneously. To solve the optimization problem, the GA starts with the structural representation of a parameter set. The parameter set is encoded as a string of finite length, called chromosome. These chromosomes are strings of zero's and one's. Genetic algorithms (GA's) [5] are mathematically motivated search techniques that try to emulate biological evolutionary processes to solve optimization problems. Instead of searching one point at a time, GA's use multiple search points. GA's attempt to find near-optimal solutions without going through an exhaustive search mechanism. Thus, GA's can claim significant advantage of large reduction in search space and time. In the present work, a new method for image compression using Fractals and Contourlet transform is proposed and the encoding method used is Genetic algorithm. The proposed method uses a simpler classification system for range blocks.

## 2 FRACTAL IMAGE COMPRESSION

A Fractal is a geometrical shape that is self-similar. Most of Fractal structures are possessed in physical processes of nature. It yields FICa exploit self-similarity in images of clouds, hills, trees, bushes and textures for compression. FIC technique represents images as iterated function systems or fractal codes that will generate the image. A gray-scale image is taken as a subset of  $R^3$  (3D vectors of real numbers). Each point represented in  $R^3$  as  $(x, y, I(x, y))$ .

An IFS is a set of mappings:  $f_1$  to  $f_n$  when iteratively applied to any initial image  $S_0$  results in a finite fixed set image  $S$ . This contractive mapping theorem guarantees the existence of such a fixed set for contractive mappings. Contractive mappings are transforms on points in

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metric spaces such that the distance between the transformed points is smaller than the original points. Affine transformations are contractive mappings used in FIC are such as :

$$Fi(x,y,z) = (ai * x + bi * y + ei, ci * x + di * y + fi, si * z + oi).$$

si is for the contrast and oi is for brightness.

### 3 CONTOURLET TRANSFORM

Down-sample input image S1 by factor 2 and low-pass filter to give image S2. Partition images are S1 and S2 classified as, range and domain blocks with block size 4X4. Each block in range image is compared with domain image with respective images. The most closest blocks are chosen( in the LMS sense) and the corresponding coefficients of transforms that would transform Block Di into Block Rj is stored in the file. Starting with any image S0, apply the affine transforms with coefficients as given in the encoded file, for several iterations. The algorithm is guaranteed to converge to an image that is similar to the original image.

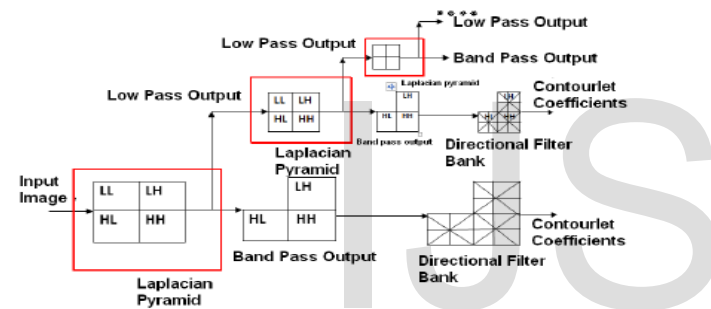


Fig. 1 The flow diagram of a contourlet transform

The contourlet transform has been introduced by Donoho and Vetterli [6], is a directional transform, which is capable of capturing contours and fine details in images. It allows for different number of directions at each scale/resolution to achieve a critical sampling. The Contourlet transform has good approximation properties for smooth 2D functions. It finds a direct discrete-space construction, and is therefore efficient in computation sense. Originally it was defined in the discrete domain, but the authors proved its convergence in the continuous domain also. The contourlet expansion is composed of basis function oriented.

With this rich set of basis functions, the contourlet transform effectively capture smooth contours that are the dominant feature in natural images. Contourlet transform is realized as a double iterated filter bank. In this transform, the Laplacian pyramid does the decomposition of images into subbands and then the directional filter banks analyze each detail image. The diagram is shown in Fig.1. The combination of this double filter bank is named Laplacian pyramidal directional filter bank. (LPDFB). The Laplacian pyramid (LP) is used to capture the point discontinuities, and it is followed by a directional filter bank (DFB) to link

point discontinuities into linear structures. By cascading multiscale and directional decomposition stages are independent of each other. First, multi scale decomposition by the Laplacian pyramid is computed where low pass channel is sub-sampled while the band pass is not sub-sampled. Then a directional filter bank is applied to each band pass channel. Each band pass image is further decomposed by DFB step. By doing this directional information can be captured. The scheme is iterated on coarse image. In Contourlet, the number of directional subbands at each level is set to  $2^n$  where n is a positive integer number. For example, if we choose to decompose an image into four levels using  $n=(1, 2, 3, 4)$  then sub bands 2, 4, 8, and 16 are got as shown in Fig.4.

#### 3.1 Laplacian Pyramids

Laplacian pyramid removes spatial redundancy .With a Laplacian pyramid we can compress data and so it would be possible to use larger data sets or to decrease the hardware requirements. The construction of one level of the Laplacian pyramid consists of 3 steps. This is shown in Fig.2. First original image is applied to Gaussian low-pass filter and then to down sampler to get a lower resolution version of the input data. Here H and G represent low pass analysis and synthesis filter .M represents sampling matrix. The outputs are a coarse approximation 'a'. This new level of the Gaussian pyramid has only the half resolution at each dimension. If we apply the inverse function we get an approximation of the original data set. If we calculate the differences 'b' between the input data and the expanded data we get the respective level of the Laplacian pyramid. The differences are nearer to 0 and are uniformly quantized and requires fewer memory to store it, but with an error involved. The error depends on the number and the distribution of the quantization levels.

#### 3.2 Directional Filter Banks

The DFB decomposition leads to sub bands with wedge-shaped frequency partitioning. The original construction of the DFB in involves modulating the input image and using quincunx filter banks with diamond-shaped filters . To obtain the desired frequency partition, a complicated tree expanding rule has to be followed for finer directional subbands. Minh N. Do and Martin Vetterli [7] proposed a new construction for the DFB that avoids modulating the input image and has a simpler rule for expanding the decomposition tree. This DFB is intuitively constructed from two building blocks.

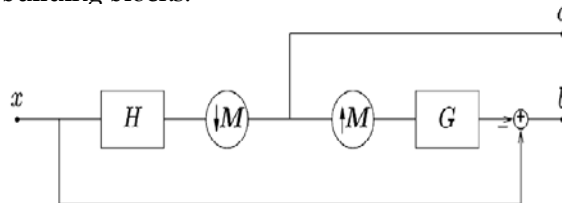


Fig. 2 Laplacian pyramid scheme analysis

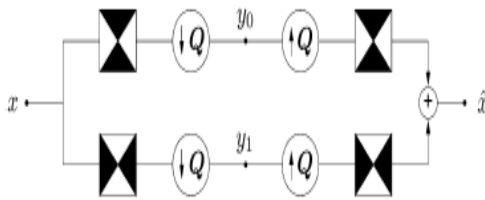


Fig. 3 Directional Filter Bank

The first building block is a two-channel quincunx filter bank fan filters Fig. 3 that divides a 2-D spectrum into two directions: horizontal and vertical. The second building block of the QFB is a resampling operator, which amounts to just reordering of image samples. Q is a matrix used to decimate the sub band signal. In two channel Quincunx filter bank, fan filters divide a 2D spectrum into two directions horizontal and vertical.

#### 4 GENETIC ALGORITHM

The GA uses a direct analogy of natural evolution process. The parameters are regarded as the genes of a chromosome and can be structured by a string of binary values. A fitness value, is used to reflect the degree of "goodness" of the chromosome to solve the problem, and this value is closely related to its objective value. Throughout a genetic evolution, a fitter chromosome yields good-quality offspring, which means a better solution to the problem. Practically In GA, a population pool of chromosomes has to be installed and they can be randomly set initially. In each cycle of genetic operation, termed an evolving process, a subsequent generation is created from the chromosomes in the current population. The genes of the parents are to be mixed and recombined for the production of offspring in the next generation. From this process of evolution, the "better" chromosome will create a larger number of offspring, and has a higher surviving rate in the subsequent generation, emulating the survival-of-the-fittest mechanism in nature. A scheme called roulette wheel selection is one of the most commonly used techniques in such a proportionate selection mechanism.

The cycle of evolution is repeated until a desired termination criterion is reached. This criterion can also be set by the number of evolution cycles (computational runs), the amount of variation of individuals between different generations, or a predefined value of fitness. In order to facilitate the GA evolution cycle, two fundamental operators-crossover and mutation-are required, although the selection routine can be termed as the other operator. for mutation, the process is applied to each offspring individually after the crossover exercise. Bit string encoding is the most classical approach used by GA researchers because of its simplicity and traceability. The chromosome is formulated in a hierarchical structure. Higher-level nodes in the structure govern the activation of the lower-level genes. The deactivated genes provide additional information that allow it to react to a changing environment. To maintain population diversity and enable searching between differ-

ent structures, the population is formulated by a number of subgroups. Each subgroup stores up chromosomes that have a particular class of structure.

#### 5 RESULTS AND CONCLUSION

The following example suggests how the Fractal Encoding can be done. Suppose that we are dealing with a 128 x 128 image in which each pixel can be one of 256 levels of gray. We called this picture Range Image. The original image reduce by averaging (down sampling and lowpass-filtering) to 64 x 64. This new image is Domain Image. We performed the following affine transformation to each block:

$$(D_{i,j}) = \alpha D_{i,j} + t_o \quad (2)$$

Where

$$\alpha = [0,1], \alpha \in \mathcal{R} \text{ and } t_o \in [-255, 255], t_o \in \mathcal{Z}.$$

In this case we are trying to find linear transformations of our Domain Block to arrive to the best approximation of a given Range Block. Each Domain Block is transformed and then compared to each Range Block  $R_{k,l}$ . The exact transformation on each domain block, i.e. the determination of  $\alpha$  and  $t_o$  is found minimizing.

TABLE 1

Image	Compression ratio	Processing time	PSNR
Lena	17.00	1.5	32.24
Pepper	18.00	1.28	32.54
Barbara	16.00	1.65	29.39
Baboon	16.00	2.95	29.2

TABLE 2  
 COMPARISON OF CONTOURLET BASED FIC USING GA

Image	method	PSNR	Speed up rate	Hit block	bpp	Time
Lena	Full search method	29.91	1.1	-	0.45	3235
	Genetic algorithm	29.94	32.23	581	0.59	1227
Pepper	Full search method	28.24	71.28	-	0.38	3145
	Genetic algorithm	29.48	81.2	583	0.43	33
Baboon	Full search method	20.15	2.35	-	0.55	1502
	Genetic algorithm	23.56	40.6	303	0.65	73

TABLE 3

COMPARISON OF CONTOURLET AND WAVELET BASED FIC USING GA

Parameter	Wavelet based FIC with GA		Contourlet based FIC with GA	
	Lena	Baboon	Lena	Baboon
Compression Ratio(bpp)	1.2:1	1.2:1	6.73:1	6.73:1
PSNR	35.29	32.6	40.05	34.98
Encoding time (secs)	7800	8435	539	447

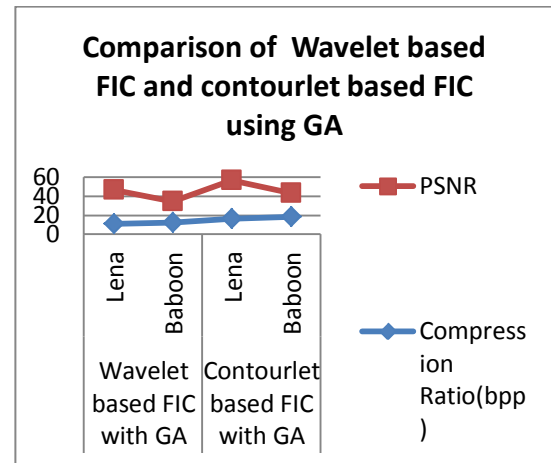


Fig. 6 Wavelet based FIC and Contourlet based FIC

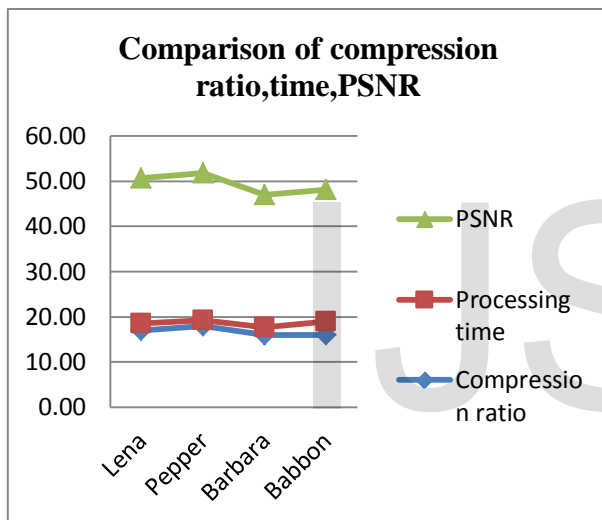


Fig. 4 Comparison of compression ratio, processing time and PSNR

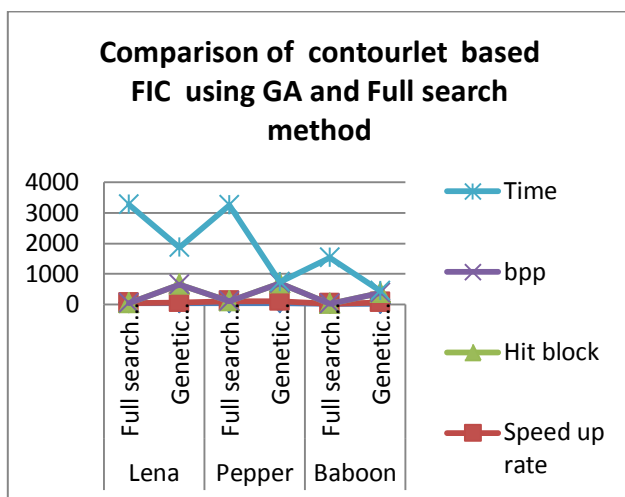


Fig. 5 Comparison of Contourlet based FIC using GA

## 6 CONCLUSION

A new FIC scheme is proposed to improve the image quality at higher compression ratio and speeding up the compression algorithm using Contourlet algorithm along with Genetic algorithm. This proposed algorithm compares the parameters BPP, CR, MSE and PSNR. By comparing the results from the contourlet and wavelet methods it is tabulated in the Table 3. Also the comparisons were done for full search method and genetic algorithm and tabulated. Thus the IFS for Fractal image compression using GA is best solution for the drawbacks such as Low compression ratio, Processing time and also provides speeding up of the algorithm.

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