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A NOVEL OPTIMIZED APPROACH OF FIC USING CODEBOOKS FOR REMOTE SENSING IMAGES

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ABSTRACT

Image compression has become a great concern in the storage and the transmission of the remote sensing image information. A new approach was used for compressing natural and satellite images by using Fractal Image Compression (FIC). The application presented in this paper is based on a novel image structure, spiral architecture which has hexagonal instead of square pixels as the basic element. The best blocks are searched by use of Particle Swarm Optimization (PSO) technique for the compression of remotely sensed imageries. The codebook approach of fractal spiral for remote sensing image compression has been used to speedup searching for similarity blocks. Compression is considered for encoding speed, quality of the image after decoding and for compression rate. PSO algorithm increases the speed of convergence for reaching the best block and then reduces the time for producing the compressed images. Experimental results demonstrate that the proposed improved fractal spiral compression approach using optimal technique for remote sensing imageries outperforms two-dimensional oriented wavelet scheme. Furthermore it is suitable for real time remote sensing images for its low computational cost.

Keywords: codebook, fractal image compression, hexagonal structure, particle swarm optimization, remote sensing image, spiral architecture.

1. INTRODUCTION

Remote sensing images are widely used in real-time geographic visualization systems and natural resource mapping/monitoring, disaster management etc. Such systems require large memories to store landscape details.Remote sensing images require a large number of bits to represent them, and if the image needs to be stored or transmitted to the ground, it is impossible to do so without reducing the number of bits for this data.In our approach we efficiently compress and decompress the remote sensing images. This leads to memory reduction. In this paper a codebook approach on fractal spiral image compression using particle swam optimization is applied for coding satellite images.

Fractal coding is one of the most efficient compression techniques. Fractal coding method finds the similarity regions in the different parts of the image, in which the image can be represented as fixed points of *Iterated Function System (IFS).* Here the image can be represented in terms of fractals rather than pixels [1]. Collage Theorem is employed for Partitioned Iterated Function System (PIFS) and it performs the encoding of gray scale images in an effective manner.

The proposal of Fractal Image Compression (FIC) was originally introduced by M.F. Barnsley and S. Demko [2]. Fractal image compression that uses the characteristics of existing self similarity [2, 3] within images is a suitable method for coding an image. Jacquin introduced fractal image encoding based on PIFS [4] later. Fractal Image coding attempts to find a set of contractive transformations that map overlapping domain cells onto a set of range cells with the aid of affine transformation. The key point for fractal coding is to extract the fractals which are suitable for approximating the original image and these fractals are represented as set of affine transformation [4]. In most cases fractal coding is applied to the gray scale images. In the case of color images gray scale fractal image is achieved by splitting the RGB values of a color image into three planes of Red, Green, and Blue. This is compressed by treating that each of the three color channel as a single gray scale image. This is called three components Separated Fractal image Code (SFC) [5].

One remarkable feature of fractal image compression is that it is resolution independent when decompressing, it is not necessary that the dimensions of the decompressed image be the same as that of original image. In traditional, the pixels in an image can be represented as a rectangular shape. In our approach each vision unit is considered as a set of seven hexagons called spiral architecture. This hexagonal image structure was proposed by Sheridan in 1996, on which each hexagonal pixelis identified by a designated positive seven-based integer [6].Here we propose a progressive texture compression system by incrementally decomposing new images into codebooks and transformation maps. Our specific contribution in this study is Codebooks. The Specific Purpose is to classify remote sensing images into different categories based on their contents, and we construct codebooks separately for each category. In each category, we use a public codebook to store common features among images, and a private codebook to store distinct contents in each individual image.

The proposed algorithm fuses the domain knowledge of image property, PSO model, and fractal coding scheme and codebooks together to achieve the speedup purpose and preserve the retrieved image quality. Compared with using a single codebook for all images, this structure is more efficient to build for large-scale images with varying contents.

The existing fractal image compression generates the code book for an image to be compressed by globally searching the matching affine transformed domain block for each range block. This require much time for image compression. This proposed approach focus on the search space reduction, speeding up the fractal image compression and preserve the image quality based on particle swarm optimization. This proposed algorithm saved the encoding time and obtained high compression ratio.

A. Previous work

Some existing methods involve fractal coding with Discrete Cosine Transform (DCT) [7] or with Wavelet transform [8], or using some classification criteria to classify range-domain blocks. A schema genetic algorithm for fractal image compression is proposed in [9] to find the best self similarity in fractal image compression. Truong *et al*. [10] proposed a kind of neighborhood matching method based on spatial correlation which makes use of the information of matched range blocks and effectively reduced the encoding time. Some other researchers have combined fractal with other algorithms such as ant colony optimization [11], neural network [12], genetic algorithm [13], fractal wavelet [8], etc. Wu *et al*. [14] proposed a Spatial Correlation Genetic Algorithm (SC-GA), which speeded up the encoding time and increased compression ratio.

Bo li *et al*. [15] proposed a 2-D Oriented Wavelet Transform for remote sensing image compression, which performs integrated oriented transform in arbitrary direction and achieve a significant transform coding gain. JPEG and other DCT based compression techniques [16] have been employed in many space missions. Pan Wei *et al.* [17] proposed 3-D Fractal coding to compress the hyperspectral remote sensing image. An improved method of remote sensing image compression based on fractal and wavelet domain was introduced by Yu Jie *et al*. [18].

Wei Hua Rui *et al.* proposed a progressive texture compression framework [19] to reduce the memory and bandwidth cost by compressing repeated content within and among large-scale remote sensing images. Wang, et al. presented [20] fractal image compression based on a novel image structure, Spiral Architecture, which has hexagonal instead of square pixels as the basic element. Spiral Architecture based fractal image compression is proposed by Huaqing Wang *et al*., to illustrate the great potential of Fractal Video Compression (FVC) on Spiral Architecture. Manoj Kumar, Poonam Saini developed a novel Vector Quantization (VQ) codebook generation method [22] based on the Linde-Buzo-Gray (LBG) is image compression technique with the major steps Codebook Design, VQ Encoding Process and VQ Decoding Process. Zhaohui li and Liang zhao presented a new fractal color image compression method, called Fractal Hierarchical Color Block Coding (FHCBC), [23] which transforms the three color planes of a color image into a one component image by extracting correlation among them. Nileshsingh V. Thakur, Dr. O. G. Kakde [24] proposed the approach Modified Fractal Coding Algorithm for Grey Level Images on Spiral Architecture (MFCSA), composes the one-plane image using the pixel's trichromatic coefficients. One-plane image in traditional square structure is represented in Spiral Architecture for compression.

PSO directs particles to search the solution more efficiently [35], [39]. Mathematical inexpensive algorithm can be implemented in a few lines of computer code [40], [41] with the PSO paradigm. Huber Fractal Image Compression (HFIC) [43] uses PSO to speedup the search of a nearestmatch block for a given block to be encoded. PSO-based FIC shows that PSO can efficiently find the suitable domain blocks and the retrieved imagequality can be preserved [42].

The rest of this paper is organized as follows. In section 2, general fractal image encoder is discussed. Section 3 discusses fractal image compression using spiral and PSO algorithm. Section 4 explains the proposed codebook approach of fractal spiral image compression. Section 5 reports the experimental results. Finally section 6 concludes this paper and draws some issues for further development.

2. GENERAL FRACTAL IMAGE ENCODER

The fractal image compression algorithm is based on the fractal theory of self-similar and self-affine transformations. The act of coding an image is in the way that at first the original one (Range Image) is divided into a set of block with identical size (Range Block). An image with less detail is also divided into blocks with identical size (Domain Block). For each block, choose a suitable block among the range blocks and transforming in the way that by applying on the range block, the produced image is to be closed to the related Domain block. For obeying the Contractive Mapping Fixed-Point Theorem, the domain block must exceed the range block in length.

The basic algorithm for fractal encoding is as follows:

- The image is partitioned into non overlapping range cells {Ri} which may be rectangular or any other shape such as triangles.
- The image is covered with a sequence of overlapping domain cells. The domain cells occur in variety of sizes and they may be in large number.
- For each range cell, the domain cell and corresponding transformation that best covers the range cell is identified. The transformations are generally the affined transformations. For the best match the transformation parameters such as contrast and brightness are adjusted.
- The code for fractal encoded image is a list consisting of information for each range cell which includes the location of range cell, the domain that map onto that

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range cell and parameters that describe the transformation mapping the domain onto the range.

Examples of affine transformations shown in Figure-1 include translation, scaling, homothetic, similarity transformation, reflection, rotation, shear mapping, and compositions of them in any combination and sequence [2].

Transformation No.	Transformation details	Representation
1	Original domain block	A B D C
2	Flip the above domain block about Y axis	B A C D
3	Rotate original domain block by +90°	D A C B
4	Flip the above domain block about Y axis	A D B C
5	Rotate original domain block by +180°	C D B A
6	Flip the above domain block about Y axis	D C A B
7	Rotate original domain block by +270°	B C A D
8	Flip the above domain block about Y axis	C B D A

Figure-1. Eight transformations used for mapping of domain blocks to range blocks.

3. FRACTAL IMAGE COMPRESSION USING SPIRAL AND PARTICLE SWARM OPTIMIZATION

On Spiral Architecture, an image is represented as a collection of hexagonal pixels. Each pixel has only six neighboring pixels with the same distance to it. Each pixel is identified by a number of bases 7 called a spiral address [22]. In the hexagonal structure pixels are not arranged in rows and columns. In spiral architecture six additional collections of seven hexagons can be placed about the addressed hexagons and multiply each address by 10. Initially we separate the image into non-overlapping range blocks of seven pixels and define the overlapping domain blocks of seven times more in general [22] as in Figure-2.

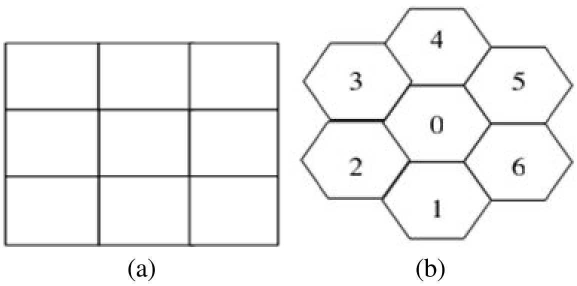

Figure-2. (a) Rectangular Architecture (b) Spiral Architecture.

A. Range and domain blocks on spiral architecture

The procedure begins with an equal-size image partitioning on SA. The number of pixels in each sub-image is a power of seven, i.e.7, 49 or 343. A sub-image can then be defined as a range block or it can be further separated into parts of similar size to obtain smaller range blocks as in Figure-3, [43] first the image is partitioned into sub-images of 49 pixels and within each sub-image two range blocks are defined.

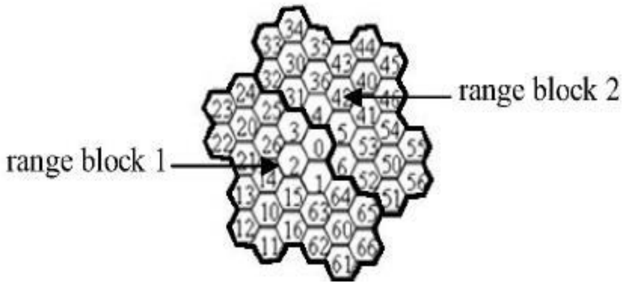

Figure-3. Two range blocks defined within a sub-image of 49 pixels.

Following the systematical scheme, range blocks can be defined quickly based on spiral counting. The sub sampled domain block can be represented as in equation (1),

$$B_i = \mu(D_i) \tag{1}$$

To form the Codebook blocks, the domain blocks are optimized to specific number, then filtered and sub-sampled using pixel median so that it shrinks to match the size of the range blocks**.** The matching between the range and domain block can be done by equation (2).

$$d^2(R_i,B_i)=\sum_{i=1}^{n}(r_i-b_i)^2 \tag{2}$$

n = number of pixels in R_i and B_i block

B. Overview of PSO

Particle Swarm Optimization is a computation technique developed by Eberhartand Kennedy [35] based on the analogy of swarm of birds and school of fish.PSO has a flexible and well-balanced mechanism to enhance the global and local exploration abilities [35]. The particle swarm simulates a kind of social optimization. PSO mimics the behavior of individuals in a swarm to maximize the survival of the species. It is similar to other evolutionary computation techniques like Genetic Algorithm (GA) in conducting searching for optima using an initial population of individuals. The individuals of this initial population are then updated according to some kind of process such that they are moved to a better solution area. PSO is motivated from the simulation of social behavior. It borrows the principle of cooperation and competition among the individuals themselves. PSO has memory, that is, every Particle remembers its best solution (Pbest) as well as the group best solution (Gbest). The advantage of PSO is that the initial population of PSO is maintained and so there is no need for applying operators to the population, a process which is time and memory-storage consuming.Each particle tries to modify its position using the information as the current positions, the current velocities, the distance between the current position and Pbest and the distance between the current position and Gbest.

The final particles represent the most optimized solutions.

PSO is initialized with swarm includingN random particles. Each particle is treated as a point in a D-dimensional space. The i^{th} particle is represented as $x_i = (x_{i1}, x_{i2}, \ldots, x_{iD})$, x_{ij} is limited in the range $[a_j, b_j]$. The best previous position of the i^{th} particle (PBEST), is represented as$p_i = (p_{i1}, p_{i2}, \ldots, p_{iD})$. The best particle among all the particles in the population (GBEST) is represented by pg= (p_{g1}, p_{g2}, p_{gD}). The velocity of particle i is represented as V_I= (v_{i1}, vi2, viD). After finding the aforementioned two best values, the particle updates its velocity and position according to the following equations:

$$Vid=v_{id}+c_1r_1\ (p_{id}-x_{id})\ +c_2r_2\ (p_{gd}-x_{id}) \quad (3)$$

$$Xid=x_{id}+v_{id} \quad (4)$$

where d is the d^{th} dimension of a particle, c_1 and c_2 are two positive constants called learning factors, r_1 and r_2 are random numbers in the range of [0, 1]. The population size is first determined, and the position and velocity of each particle are initialized. Each particle moves according to (3) and (4), and the fitness is then calculated. Meanwhile, the best positions of each particle and the swarm are recorded. Finally, as the stopping criterion is satisfied, the best position of the swarm is the final solution.

In order to reduce the amount of data used in encoding phase, the proposed method uses PSO to screen out the insignificant domain blocks, and then eliminates those blocks. The steps of modified fractal encoding according to the proposed reduction method are,

- The image is split into D domain blocks of size (L X L) and R range blocks of size (N X N) for fractal encode.
- Set the swarm size must be proportional to (N-2L+1)2/ (maximum no. of iterations for PSO) and initialize the each particle velocity and the position randomly.
- By using eqn. (23) the fitness value of distance between domain block and range block specified by the particles position and given range block.
- Update swarm best position if the fitness of the new best position is better than that of the previous swarm.
- If swarm best position is not changed for some percentage of maximum iteration for PSO, then stop.
- The best position of the particles is updated and goes to step 3.

PSO repeatedly performs the calculation of the objective function (MSE) for each of the particle in the current population i and then updates the particle coordinates based on (3) and (4). These two steps are repeated from population to population until a stopping criterion terminates the search. At the end of last iteration the Gbest domain value is noted from the Pbest domain values and utilizing the Gbest domain value, the domain block matching for the range block is done.

C. Codebook construction

There are two types in codebook. We use a public codebook to store common features among images, and a private codebook to store distinctive contents in each individual image. Compared with using a single codebook for all images, this structure is more efficient to build for large-scale images with varying contents. Compared with using a single codebook for all images, this structure is more efficient to build for large-Scale image. The basic idea behind this system is to incrementally update the contents in codebooks, if and only if its content is not sufficient to recover a new image. This dynamic feature is used to reduce the computational cost when dealing with a varying data set of multiple image scale images with varying contents. A public codebook is used to recover multiple images during the decompression process. A simple solution here is to directly insert new contents into a single codebook when the system receives a new image. However, it is likely to produce a huge codebook and slow down the compression process. So we propose to use two codebooks instead of one. We use a public codebook to contain common contents among images and it will be used to recover multiple images during the decompression process. To further reduce the public codebook size and accelerate the codebook construction process, we classify remote sensing images into different categories and construct public codebooks separately for each category.

4. PROPOSED ALGORITHM

For the encoding of any color image, the whole encoding process is divided into two parts. First, the one plane image formation and average trichromatic coefficient calculation of relevant homogeneous blocks which formed according to the tolerance value. Then only one color-plane needs to be coded, while the other two can be automatically reconstructed from the encoded color plane and correlation among them.

- Read input images from the database. The image may be in the form of landsat format.
- Find RGB mean of the color images to convert into grayscale images.
- Split input image.
- Construct spiral architecture and find domain blocks and range blocks
- Optimize the blocks using Particle Swarm Optimization.
- Resize domain block to range block size for mapping.
- Set to range block nearest domain block.
- Compute fractal image compression by forming public, private code books and transformation maps.

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- Decode the image by applying fractal image decompression with the public and private code books and with the transformation map.
- Calculate PSNR and compression rate, Mean Square Error and Structural Similarity Index.

We use a private codebook to store and recover distinctive contents in each image. Finally with the aid of affine transform range block is mapped from their best domain block in the codebook.

Given a new image and an existing public codebook, we take the following steps to update the public codebook and construct a private codebook. We first separate the image into a set of blocks, each of which contains 16×16 pixels. We then run similarity search between each image block and the public codebook [19]. If a match exists, we compute and store the appropriate transformation, with which the block can be directly recovered from the existing codebook. For these remaining blocks that cannot be represented by the public codebook, we build a similarity match list for each block as in [6] and count how representative a repeated content is. If the reused times are more than a threshold, the block will be added into the public codebook bank. Otherwise, we think it is not representative enough and it will be assembled into the private codebook instead. Details on the assembling process can be found in [6].

5. EXPERIMENTAL RESULTS AND DISCUSSION

Landsat TM images of 512x512 sizes are taken from USGS Global. The data is carried out using ERDAS IMAGINE image processing software. In this section, the proposed PSO-based fractal spiral compression with code book approach is simulated and verified. In the simulation, six remote sensing images are used for test as large scale. The number of iterations for PSO is 100 and particles size is set to10. Table-1 reflects the results of Peak Signal to Noise Ratio (PSNR), Structural Similarity Index Measure (SSIM) and Mean Square Error (MSE) for the six remote sensing images using the proposed approach.

The codebook sizes of public and private and the encoding time and decoding time are listed as side information in Table-2. Also the table reveals the computation time for compression and decompression in seconds. The distortion between the original image f and the retrieved image f' caused by lossy compression is measured in peak signal to noise ratio defined by the equation (5).

$$PSNR(f, f') = 10.\log_{10}\left(\frac{255^2}{MSE(f, f')}\right) \quad (5)$$

The similarity between two image blocks and of the same size LxL is measured in terms of the mean squared error defined by equation (6).

$$MSE(u, v) = \frac{1}{L^2}\sum_{i,j=0}^{L-1}[u(i,j) - v(i,j)]^2 \quad (6)$$

SSIM is a more appropriate image quality measurement for the Human Visual System. SSIM between two images is the mean of the SSIMs between local corresponding blocks. SSIM(x, y) $\in$[-1, 1] gets its best value 1 when x=y. The bigger the SSIM is, the more similar the images are.

To optimize the codebook, the concept of PSO is used with spiral architecture which improves searching time, in turn speedup and guard the image quality. The concept of particle swarm optimization is used with the intension of overcoming the disadvantages of searching blocks. Fora given block to be encoded Particle Swarm Optimization speeds up the search of a near best match blocks.

Table-1. Performance of remote sensing mages using proposed scheme.

Image	**PSNR** (dB)	**SSIM**	**Bpp**	**MSE**
Metropolis	28.8203	0.8817	0.6549	79.4000
Industry	27.2573	0.8656	0.6549	122.2780
Capital	36.6712	0.9812	0.6547	13.9940
Urban Land	35.4805	0.9234	0.6547	18.4000
Low Land Crop	33.7908	0.9306	0.6549	27.1640
Vegetation Area	32.7072	0.9238	0.6549	34.8601

For fractal coding, eight MSE computations between a domain block and a range block are needed due to the eight Dihedral transformations performed on. A Matlab implementation of which is available online at [46]. Figure-4 plots the performance variation in PSNR for the six remote sensing Images. Of the six remote sensing images, the Capital image having high PSNR value.

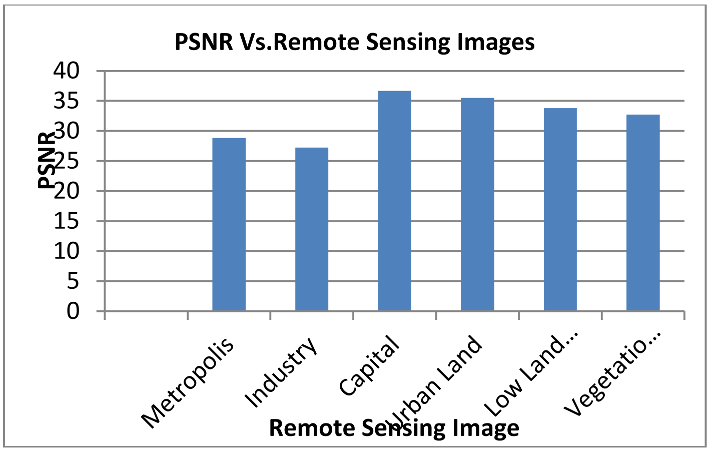

Figure-4. Performance in PSNR for remote sensing images.

Table-2 presents the side information calculated for the proposed scheme in terms of bytes of public codebook size, private codebook size and encoding, decoding time in seconds.

Table-2. Code book size, encoding and decoding times using proposed scheme.

Public code book size (bytes)	**private code book size** (bytes)	**Encoding time** (sec)	**Decoding time** (sec)
469044	6914460	2332.3874	178.9034

Table-3 compares the PSNR, SSIM and Bits per Pixel (Bpp) values for JPEG2000, 2D-OWT and the proposed FIC spiral with particle swarm optimization using codebooks. Reconstructed metropolis remote sensing image for the proposed fractal spiral with PSO using codebook is increased to 0.4003dB over JPEG-2000 and 0.1803dB increased than the 2-D OWT scheme. For the urban land image, the PSNR value is 34.51 for the JPEG-2000 and 35.4815 for the proposed scheme. There is an increment of 0.9705 over JPEG-2000 and scheme 0.5405 over 2-D OWT scheme. There was further enhancement in PSNR, but the time complexity of the algorithm turns to be much higher. Proposed Fractal spiral compression with particle swam optimization using code books gains an average of around 0.3578dB over 2-D OWT and 0.7112dB over JPEG-2000. Moreover the proposed algorithm is still performing at medium bit rate than the existing JPEG-2000 and 2-D OWT, at an enhancement of 0.3451 Bpp. This is why because of the particles search in the landscape by following the directions of blocks with similar edge property and jumps away from the regions of blocks with different edge types and therefore improves the performance of the coder.

Compression ratios will increase with respect to the number of images and the spatial complexity of the images. Also the experiment is carried out for different area remote sensing images. Table-4 reflects the performance parameters for different land cover types of remotely sensed images as Area1 (River ridge), Area2 (agricultural), Area3 (swamp), Area4 (water), Area5 (forest) and Area6 (mixed area with roads and vegetation). The efficiency of the algorithms was evaluated. From the parameters decompression time, public and private code book size, compression ratio and peak-signal to noise ratio, it is obtained that the lower spatial complexity images have high compression rates.

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Table-3. Comparisons of compression performance on Psnr (In Decibels).

Image	Size	Existing system						Proposed system			
		JPEG-2000			2-DOWT			Fractal Spiral PSO Codebook			
		PSNR (dB)	SSIM	Bpp	PSNR (dB)	SSIM	Bpp	PSNR (dB)	SSIM	Bpp	MSE
Metropolis	512x512	28.42	0.8682	1.0	28.64	0.8802	1.0	28.8203	0.8817	0.6549	79.4000
Industry	512x512	26.49	0.8497	1.0	26.92	0.8656	1.0	27.2573	0.8656	0.6549	122.2780
Capital	512x512	35.97	0.9505	1.0	36.04	0.9541	1.0	36.6712	0.9812	0.6547	13.9940
Urban Land	512x512	34.51	0.8913	1.0	34.94	0.9041	1.0	35.4805	0.9234	0.6547	18.4000
Low Land Crop	512x512	32.98	0.9109	1.0	33.45	0.9209	1.0	33.7908	0.9306	0.6549	27.1640
Vegetation Area	512x512	32.09	0.9086	1.0	32.59	0.9147	1.0	32.7072	0.9238	0.6549	34.8601

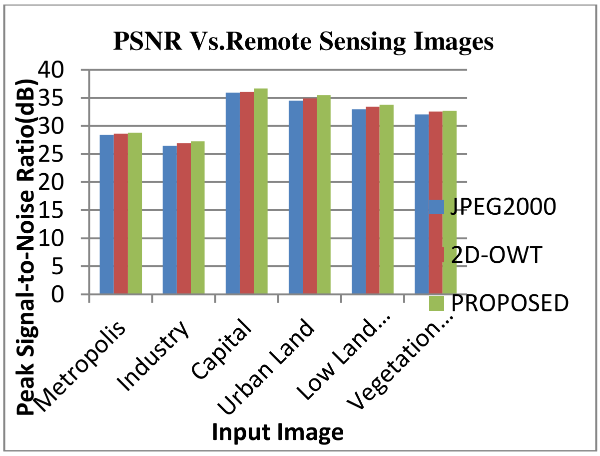

Figure-5. Comparison of PSNR of the reconstructed images.

Comparisons of PSNR of the reconstructed images are shown in Figure-5. It compares the PSNR between Jpeg2000, 2D-OWT and proposed method. Figure-6 presentsthe variations of structural similarity for the six remote sensing images using fractal compression with particle swarm optimization using codebook for the remote sensing image.

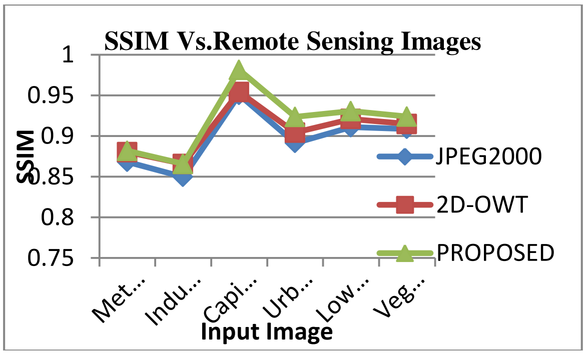

Figure-6. Performance comparison for remote sensing images on SSIM.

Compression ratios will increase with respect to the number of images and the spatial complexity of the images. Also the experiment is carried out for different area remote sensing images. Table-4 reflects the performance parameters for different land cover types of remotely sensed images as Area1(River ridge), Area2(agricultural), Area3(swamp), Area4(water), Area5(forest) and Area6(mixed area with roads and vegetation). The efficiency of the algorithms was evaluated. From the parameters decompression time, public and private code book size, compression ratio and peak-signal to noise ratio, it is obtained that the lower spatial complexity images have high compression rates.

Table-4. Performance parameters for different land cover types.

Image	Codebook Size (bytes)		Encoding time (sec)	Decoding time (sec)	Compression ratio	PSNR (dB)
	public	private				
Area1	698112	5332800	2056.4781	232.5314	53.1789	24.0064
Area2	608424	5524296	2607.0692	227.066	69.2439	25.0258
Area3	581760	5531568	3000.7283	226.6773	85.3582	31.3090
Area4	321180	4148676	2150.5962	227.7323	67.0973	24.3421
Area5	504192	5531568	2083.065	225.5102	67.0973	28.2863

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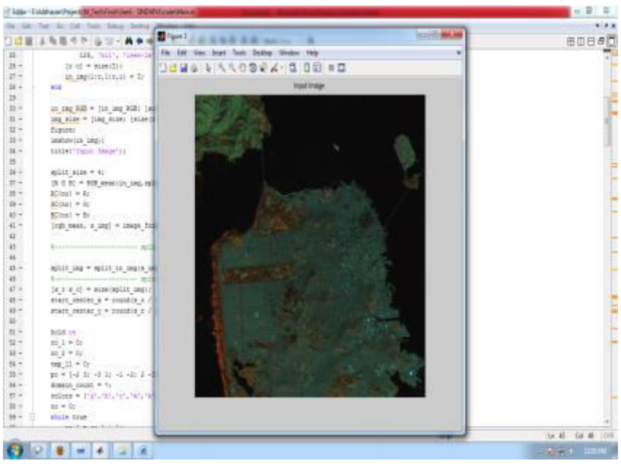
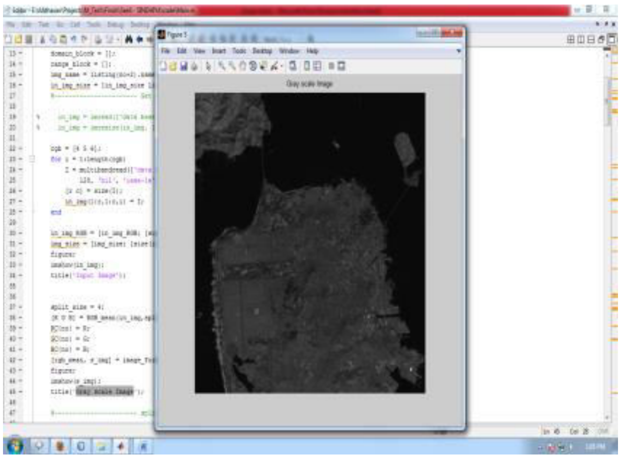
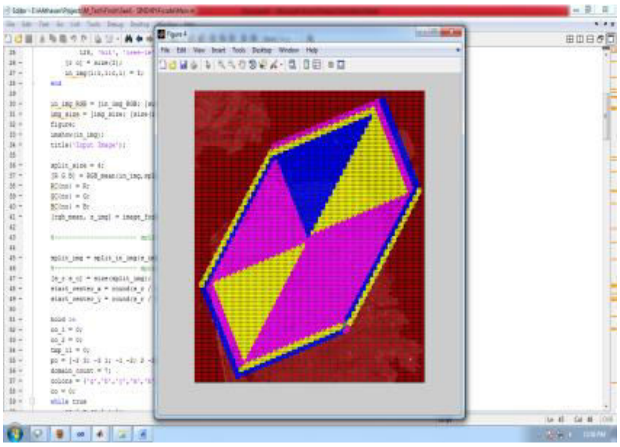
The image quality can be preserved and better visual effect can be achieved since the classifier is performed according to the edge property. Figure-7 shows the reconstructed images of metropolis using the fractal spiral partitioning with particle swarm optimization using codebook. Fractal coders can perform very well in terms of bit rate and PSNR for satellite images. From the analysis, the fractal coding techniques with spiral and PSO can be applied for achieving high compression ratios and better peak signal-to-noise ratio values for satellite images. The PSNR of the landsat images indicates that the images are of good acceptable quality for remote sensing images and the objective measures are close to the optimum values.


(a)


(b)


(c)

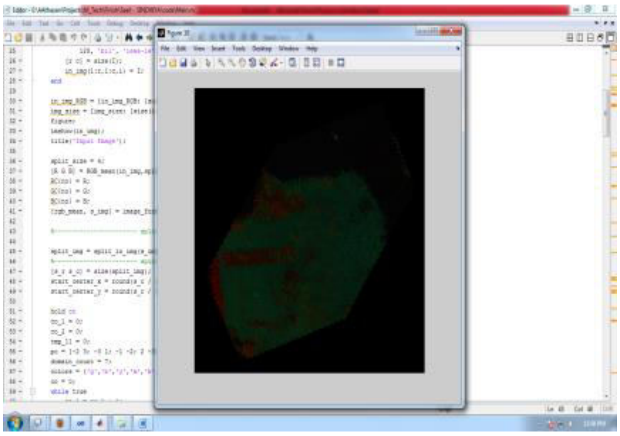

(d)

Figure-7. Screen shot images of fractal with spiral (a) original image (b) Gray scale image (c) spiral coded image (d) compressed image.

6. CONCLUSIONS

In this paper spiral architecture with PSO optimization and codebook for compressing remote sensing images has been developed. The proposed compression scheme is mainly designed for remote sensing images. According to the experiments, the search of domain blocks for the spiral codebook is by using Particle Swarm Optimization, and it is found that the spiral architecture with PSO optimization and codebook has great potential in improving fractal image compression. In our approach we introduced simple code book generation for a large scale image in order to increase the compression ratio. The replacement of traditional square structure by the spiral architecture achieve better compression ratio. In our approach we used fractal compression and two code books on the spiral architecture results good compression rate. Here we used six remote sensing images as input; instead of using separate codebook for these six images we used only two codebooks because, remote sensing images will have more similar regions. Findings of this study expose that, firstly, the proposed method presents better PSNR and good compression rate in comparison with the previous compression methods such as JPEG2000 and 2-DOWT for remote sensing images. Secondly FIC spiral with PSO codebook can be applied to compress and decompress remote sensing images. Optimization of domain blocks gives rise to have the more accuracy in the formation of codebook blocks and save the processing time.

In our future work the following issues can be further investigated. First, the limitation of spiral addressing is lack of capturing hexagonal grid. For the square images, the spiral architecture ignores the corner of the images. Trying to imitate the hexagonal grid on rectangular grid itself is the in progress research. This can be resolved to obtain the square decoded images. Second, our approach can be further applied with varying number of iterations and particle sizes. More images having different degree of complexity will need to be analyzed with more quantifiable parameters. Third, this study can be extended to kinds of remote sensing images from different platforms such as SPOT, RADAR, IKONOS etc., and for different band images. The proposed approach can be useful for the huge image data transmission where the image quality does not matter much for example, video conference.

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