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A Spiral Architecture Based Variable Range Fractal Image Compression Method

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Abstract

Fractal Technique in Image compression is a popular method applied for locating self similarity in image through range blocks and domain blocks of rectangular shape partitions. Spiral architecture (S.A) variable range image compression fractal technique is presented here, with hexagonal shape Range blocks to find similarity for best domain block match. The presented hybrid method when applied to grey test images of different categories, demonstrates improvement in image parameters like Compression Time, Peak to signal noise ratio and Compression Time. Presented method splits the image into non over lapping range block of 7 size each and using spiral count operation searches suitable larger Domain block which is a multiple of 7.Larger domain range once located is transformed and shrink resulting in better compression and image parameters. Experimentation is performed on test standard size 512X512 images of Lena, MRI, Remote Satellite, Baboon, Bird, Rose and Pepper. Our method implemented is expected to increase performance of fractal compression parameters by maximum of 10 to 12 %.

Keywords: *Spiral Architecture, PSNR, Fractal Image compression, Compression rate, iterated functions & Block domain ranges*

1 Introduction:

Image compression plays a vital role in applications related to networks and data transmission considering the huge amount of image data shared through online. The growing demand for social multimedia data sharing digitally, in more effective way through image frames and video streaming has lead to new research techniques in the area of digital compression. Detection and restoration of images for synchronized digital applications can drastically decrease the image storage size and increase its speed of transmission with reduced bandwidth. One such capable technique is Fractal image compression which works on contractive transforms [1].Fractal image compression (FIC) is based on 8 affine transforms used on original image symmetrically to encode and reconstruct compressed image in the block form[2] In conventional fractal encoding, the image to be compressed is partitioned to two sets of sub blocks. One is called Range (Rg), and the next called Domain (Dm). The entire input image is separated into non overlap Rg block of equal size and overlap Dm blocks of at least double the Rg size.

Symmetrical Affine transforms use mapping distance between two points of a transformed image to find similarity of the same distance on the original image [3] through iterated function system. Baseline FIC achieves good compression ratio(C.R) for images having more similarity content in them and it is independent to input image resolution, but exhibits long compression time and reduced PSNR in images having less similarity. The Spiral Architecture Based Variable Range (SABVR) Fractal method proposed here is expected to decrease computational Compression Time (C.T) and improve Peak to Signal Noise Ratio(PSNR) as compared to other existing techniques[4].

The paper presents an algorithm on variable Range (Rg) block image search based on spiral architecture proposed by Sheridan [5]. It focuses on Spiral approach search for Rg-Dm match with FIC maintaining Image fidelity constraints in the existing methods. Paper is ordered as per the following sections next section presents literature review, section 3 discusses the proposed Spiral Architecture Based Variable Range algorithm. Section 4 implementation with results obtained, section 5 conclusions of our findings with future research directions.

2 Related Literature Work

2.1 Baseline Fractal Image compression

The Typical Baseline FIC works on dividing the image into equal size square Rg blocks and unequal size overlapping Dm Blocks. Shrinking of Dm-Rg match is shown in the figure 1.Dm blocks get shrink to Rg size block averaging the best pixel match. Every Rg block covering the entire image is approximated by transformed Dm Pool with a brightness coefficient B[4]. The reconstructed Dm blocks adjust the pixel contrast by a contrast coefficient C. Each Rg block is represented by modified Rg Dm match for a I block as

$$Rg' = B*Dm + C*I \qquad (1)$$

In spiral architecture based [6] image partitioning the Rg blocks are divided into hexagonal shape partitions as shown in figure 2 compared to traditional square or rectangular blocks[7].

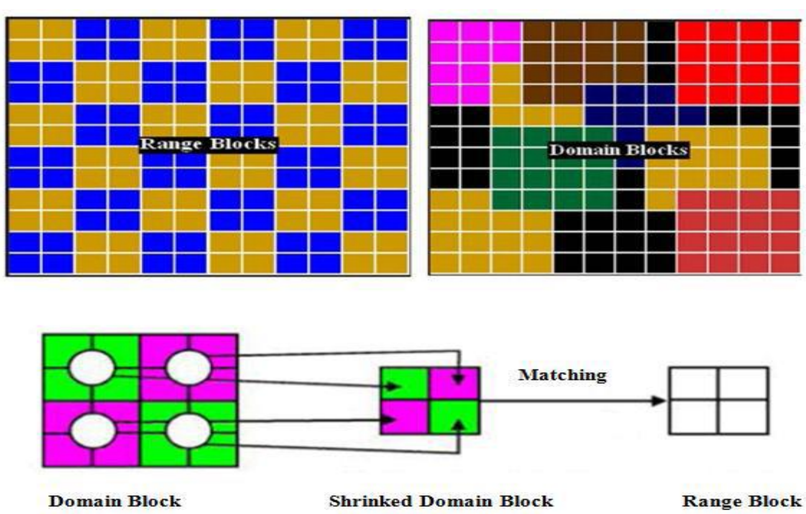

Figure 1: Schematic Diagram Showing Domain Search Match with Range

Figure 2: Image block traditional and spiral partitions

The Image quality is maintained by the 8 transform matrices [8] used for generating the Dm pool shown in Table 1.In base line FIC Rg search is the major factor that affects the encoding speed [9]. A traversal method is applied for match search which moves in uniform straight direction causing more time complexity. In the other case of spiral search shown in fig 3 Rg block search for domain takes a spiral traverse method for fast and smooth search. The search process is represented as per equation (2) of Rg-Dm match minimisation

$$E(Rg, Dm) = \| Rg-(B^* Dm + C * I) \| \quad (2)$$

The entire coded image is saved as transformed Rg match R' covering all Rg blocks. As a result C.R improves and the same iterative reverse process is used for image decoding Jacquin et al[1]. Matching decoded image is measured from its Mean Square Error (MSE) with the normal image represented in equation 3.

$$MSE = \|(P_k * Dm_k + Q_k * I - Rg_k)\| \,|| \quad (3)$$

Where P_k and Q_k are least MSE coefficients shown in equation 4 & 5

$$P_k = \frac{B^2 < Dm_k, Rg_k > - < Dm_k,\ I >< Rg_k,\ I >}{B^2 < Dm_k, Dm_k > - < Dm_k,\ I >^2} \quad (4)$$

$$Q_k = \frac{< Rg_k,\ I > - < Dm_k,\ I >}{B^2} \quad (5)$$

Table 1 shows matrix transforms applied for choosing smallest Dm block expressed in equation (6) as λ a relative compression coefficient for each Rg[10].

i.e $\lambda = \{Dm_k(p,q), T_k, P_k, Q_k)$. Where $Dm_k(p,q)$ represents the Dm'start position and T_k represent the corresponding affine transform from table 1.

Table 1 Relative Affine Transforms For Deformed Domain Block

$T_0 = \begin{pmatrix}1 & 0\\0 & 1\end{pmatrix}$	$T_1 = \begin{pmatrix}0 & 1\\-1 & 0\end{pmatrix}$	$T_2 = \begin{pmatrix}-1 & 0\\0 & -1\end{pmatrix}$	$T_3 = \begin{pmatrix}0 & -1\\1 & 0\end{pmatrix}$
$T_4 = \begin{pmatrix}-1 & 0\\0 & 1\end{pmatrix}$	$T_5 = \begin{pmatrix}1 & 0\\0 & -1\end{pmatrix}$	$T_6 = \begin{pmatrix}0 & -1\\-1 & 0\end{pmatrix}$	$T_7 = \begin{pmatrix}0 & 1\\1 & 0\end{pmatrix}$

For every Rg block, one of the best Dm block match is found by relative changes λ_i as per equation (6).

$$\lambda i \begin{bmatrix}p\\q\\z\end{bmatrix} = \begin{bmatrix}ai & bi & 0\\ci & di & 0\\0 & 0 & Ci\end{bmatrix}\begin{bmatrix}p\\q\\z\end{bmatrix} + \begin{bmatrix}ci\\fi\\Bi\end{bmatrix} \quad (6)$$

In above relative changes of λ_i, C_i is the contrast scaling coefficient and B_i represents and controls offset brightness shown in equation 7 and 8 .Later the Dm blocks are sub samples and filtered for each code book Dm block finding B and C coefficients using regression on least square error[11].

$$C = \frac{[n\sum_{i=1}^{n} Dm_i Rg_i - \sum_{i=1}^{n} Dm_i \sum_{i=1}^{n} Rg_i]}{[n\sum_{i=1}^{n} Dm_i^2 - (\sum_{i=1}^{n} Rg_i)^2]} \quad (7)$$

$$B = \frac{1}{n}\left[\sum_{i=1}^{n} Rg_i - B\sum_{i=1}^{n} Dm_i\right] \quad (8)$$

2.2 Spiral Architecture Block Compression

Spiral Architecture (SA) image represents a hexagon shape block and each unit in a group of 7 hexagons as shown in figure 3. Each pixel is allotted a positive integer for identification called as spiral address. Figure 3 shows each unit with 7 spiral addresses forming the multiple of 7 sizes. These hexagons form the recursive approach along a spiral direction for their search[12].

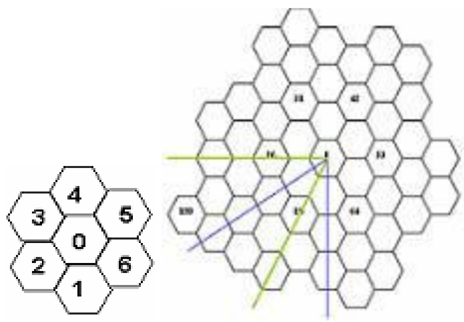

Figure 3 Multiple of 7 hexagon blocks with individual addresses

After assigning addresses to the hexagons in each unit, Next step in SA is spiral counting used to determine number of units and there flow of spiral path on each unit. Spiral counting is used to initiate and terminate a certain hexagon element search smoothly [13[14]. Pre-determined key for spiral count is calculated from the distance and orientation of each hexagon block. Figure 4 shows key establishment for 15 hexagons for each unit block count [15].

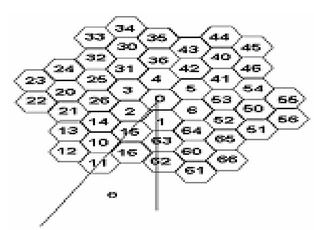

Figure 4 Key generation hexagon unit for 15 patterns of 8 hexagons

Spiral count describes Addition and multiplication operations corresponding to translation and rotation transforms of FI [16].Consider i and j to be hexagonal addresses, then there addition operation on SA is represented as i+ j where j will be spiral count hexagon with key as 1(Ex 3+2=26).Similarly multiplication operation denoted as i*j spiral count for j hexagon with the key for i address will be 0(Ex 15*2=26)[17].

In proposed method combination of SA and FIC, the image is divided into Rg block of 7 pixels and Dm of at least more than 7 is located (Ex 49) as shown in figure 5.Every pixel is considered as center of Dm

Block and neighboring 48 forming Dm pool. Using spiral count current Rg is searched from the formed Dm pool [18][19]. Figure 5 shows Rg-Dm comparison search for a 49 element.

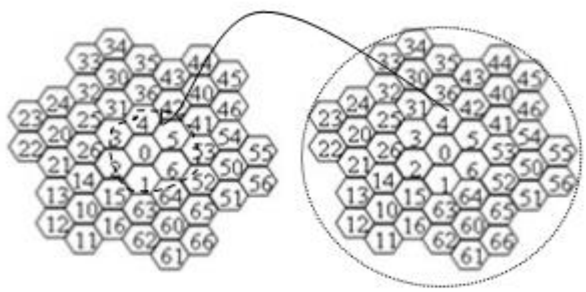

Figure 5. Range and Domain blocks in SA

3 . Proposed Spiral Architecture Based Variable Range Method

Proposed SABVM method is based on varying size of Rg block. The size of Rg considered is multiple of 7 Dm size. The two addition and multiplication operators decide the addresses of each hexagon unit. The input image is divided into 7 unit each Rg block and Dm in 49& 343 unit blocks as shown in figure 6.

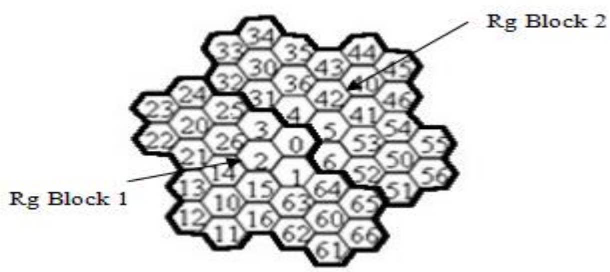

Figure 6 Range blocks in a sub block of 49 hexagons

Figure 7 shows schematic diagram of SABVR method for FIC with the following steps

i. Partition the input grey image into hexagon shape units as Rgi.

ii. Partition the input image obtaining Dm_j blocks for 343 and 49 overlapping hexagonal units of Rgj.

iii. Compute average intensity value for each Dm with 7 clustered hexagonal Rg unit resulting a new cluster of Dm_j represented by AgDm.

iv. Select the initial 10 Dm havening minimum distance and offset as per equation 7 and 8 from 343 Dm pool.

v. Generate a code book(Cb) match with Rg.Dm= [Ag (Rgi)-Ag (Dmj)], for initial 10 Dm

vi. Use median to find Dm blocks Cb from Rg found in earlier step v

vii. For each and Cbk, compute offset and scaling coefficients using affine transforms of translation and rotation from table 1 using least square technique.

viii. Compute *C* contrast scaling B offset brightness for quantified new Dm pool

ix. Find MSE using equation 3 from all Cb s with minimum error identified as min E[(Rgi),(Cbk]

x. Changing Rg size in iterations of 7 ,49 and 343 repeat steps i to x

xi. Generate Cb s of current Rg with variation in C and B coefficients by index identification for 3 iterations to obtain optimum Cb block as SABVR compressed image.

xii. Calculate the PSNR and CR by equation 9 and 10 for the reconstructed image by inverse mapping B & C coefficients.

xiii. Compute the average C.T by taking mean time of each iteration required in mapping Dm-Rg as compression time elapsed for proposed SABVR method.

$$PSNR = -10 \log \frac{\sqrt{\sum_{i,j}(\text{input image pixels} - \text{reconstructed image pixels})^2}}{\text{total pixels in input image}} \quad (9)$$

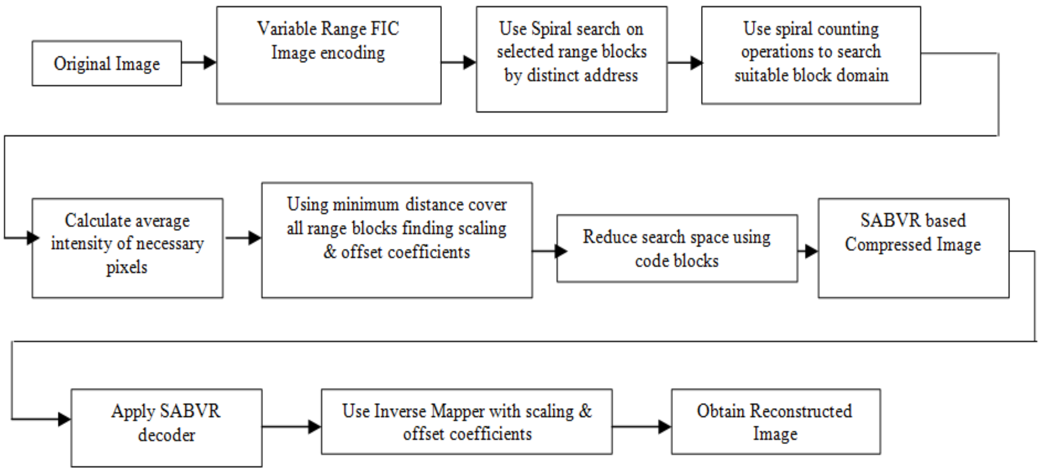

Figure 7 Block diagram of Spiral Architecture Based Variable Range method

$$C.R = \frac{\text{Size of input image}}{\text{Size of decoded image}} \quad (10)$$

The proposed algorithm is implemented using spiral operations on Rg Blocks to find corresponding Dm Blocks irrespective of their bock size[20-22]. It follows an equidistant space and non overlap condition of Dm ensuring image fidelity and independency of image resolution in decoding [23-24].

4 Experimental Implementation

SABVR algorithm is implemented on Matlab 2018b with Intel Core-i7 PC of 8GB memory. Compression Time (C.T) is recorded for encoding process by “tick tock” function. Comparative charts of proposed SABVR with Basic FIC[3] and conventional Spiral Architecture (S.A) [7]methods are plotted for compression metrics of P.S.N.R, C.R & C.T in figures 8, 9 & 10 respectively. The developed SABVR algorithm is tested on Baboon, Bird, Rose, MRI, Lena, Pepper images of size 512X512X8 and satellite urban and rural images of 2030 X 2180X8. Table 2 shows results obtained comparing with other methods.

Table 2 Comparative Results

S. no	Image Type	Technique	PSNR	CR	CT (Secs)
1.	Standard Lena	FIC	24.90	12.32	108.8
		SA	37.63	15.64	100.11
		SABVR	38.61	19.01	95.90
2	Rose	FIC	23.34	16.23	111.10
		SA	24.45	16.89	113.08

		SABVR	24.90	17.45	108.12
3	Bird	FIC	22.65	19.65	98.08
		SA	21.98	19.87	97.56
		SABVR	22.89	21.86	94.05
4.	Pepper	FIC	25.12	8.88	112.02
		SA	34.81	17.05	81.78
		SABVR	37.21	19.10	73.20
5.	Baboon	FIC	30.32	9.03	230.86
		SA	29.89	13.04	220.01
		SABVR	39.5	17	199.86
6.	MRI(Medical)	FIC	28.31	163	212.83
		SA	25.78	183	110.12
		SABVR	30.02	196	106.09
7.	Satellite urban	FIC	24.03	9.18	340.09
		SA	29.01	13.12	311.54
		SABVR	39.01	17.08	258.87
8.	Satellite Rural	FIC	20.87	8.65	290.65
		SA	23.56	9.07	265.32
		SABVR	23.89	12.08	248.65

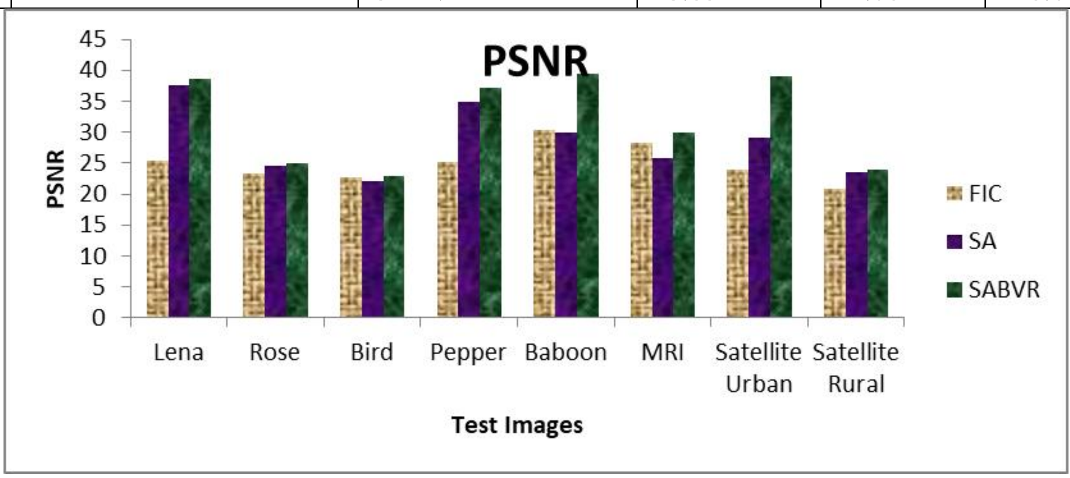

Figure 8 Comparative Results of PSNR

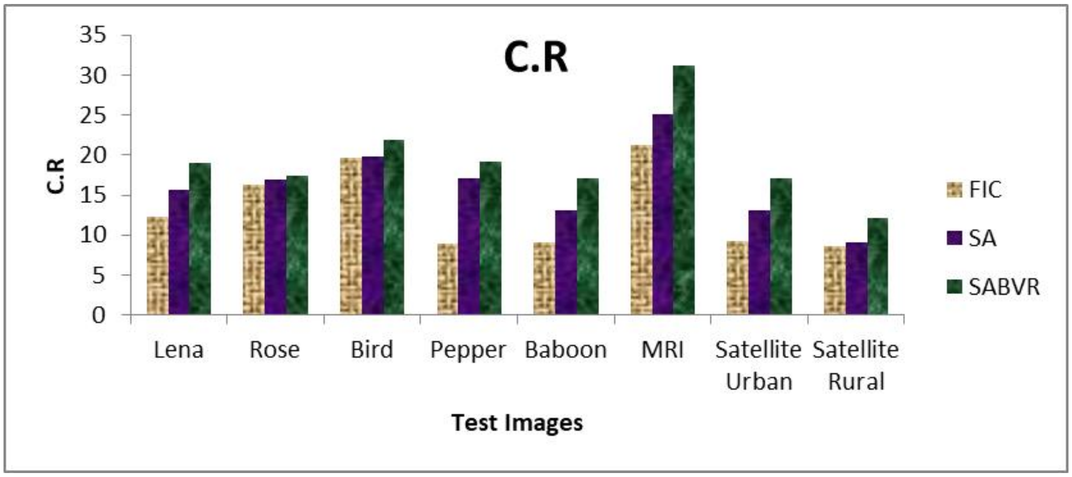

Figure 9 Comparative Results of Compression Ratio

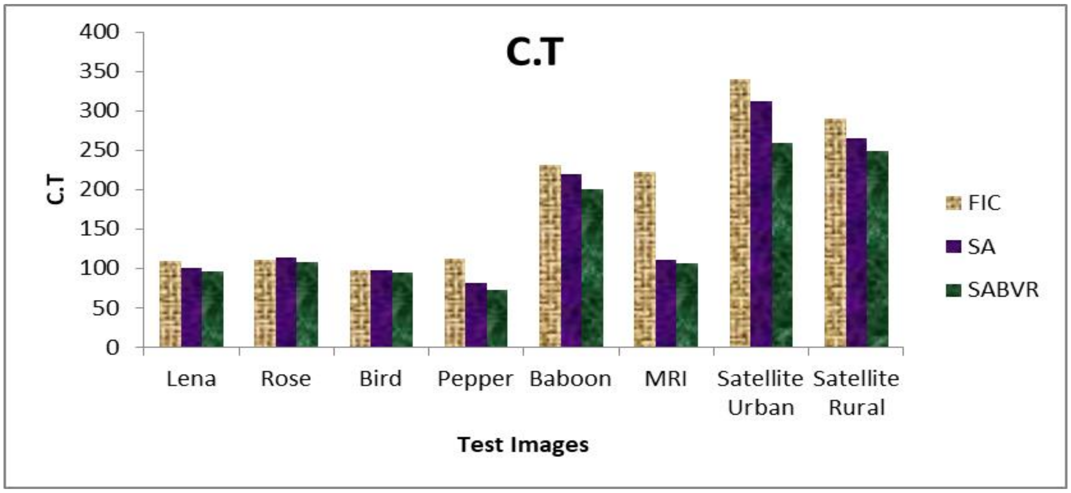

Figure 10 Comparative Results of Compression Time

5. Conclusions and Future Scope

Our Implementation results of SABVR method with existing FIC & SA proves better fidelity, improved PSNR and CT by an average of 10% and 5% respectively. Original input their reconstructed image is presented in figure 8 & 9.Results from Table 2 shows average of 8 to 9% improved C.R. This work can further be extended with machine learning and optimization algorithms to decrease Rg-Dm searches and minimize MSE errors. The involvement of nature inspired algorithms in machine learning for fractal image compression for specific medical application like MRI or CT scans is a major thrust area of research. Our SABVR algorithm can be combined with evolutionary algorithms further improving image compression metrics.

Figure 11 Input image(a) Std Lena (b) Pepper (c) Baboon (d) MRI (e) Satellite

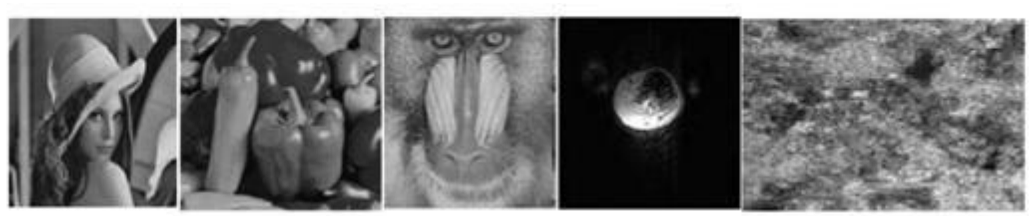

Figure 12 Reconstructed Image (a) Lena (b) Pepper (c) Baboon (d) MRI (e) Satellite

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