Normalized Gaussian Distributive Wavelet Transformation Based Iterated Functional Fractal Compression for Satellite Image Quality Enhancement

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Abstract

Compression is a fundamental processing step in computer vision applications that efficiently stores and transmits the images while preserving the better possible quality. Satellite image compression is an essential process since the systems generate a large size of high-resolution images, which directs to higher memory requirements and higher capability of communication links. Images transmit from one device to another and the receiver gets the image with poor quality due to inefficient compression rates. The existing compression techniques face major challenges to improve the quality of the reconstructed image with minimum time. In order to enhance the quality of the image, a novel image compression technique called Normalized Gaussian distributive continuous Wavelet Transformation based Iterated Functional Fractal Compression (NGWT-FC) technique is introduced. The main aim of the NGWT-FC technique is to perform efficient satellite image quality enhancement with a higher compression ratio**.** In NGWT-FC**,** numbers of satellite images are collected from the input database. After that, image compression is performed to minimize the storage complexity by minimizing the unrelated and unnecessary parts of the image. First, the input satellite image is decomposed into domain and range blocks using Normalized Gaussian distributive Ricker wavelet transformation. After the decomposition, the Fractile contraction mapping between the domain and range blocks is performed using iterated function system (IFS). An IFS explains the two-dimensional set with a fixed point of Hutchinson Operator. Finally, the encoding process is performed to convert the image parts into mathematical data termed as fractal codes. After the compression, the Fractile decompression algorithm converts the encoded image into readable form. In this way, an efficient image quality enhancement is carried out with a higher compression ratio. Experimental evaluation is carried out using satellite images with different factors such as Peak signal-to-noise ratio, compression ratio, compression time, and space complexity with respect to a number of satellite images. The observed qualitative and quantitatively analyzed result confirms that the proposed NGWT-FC technique achieves higher Peak signal-to-noise ratio, compression ratio with a minimum time as well as space complexity rate than the state-of-the-art methods.

Keywords: Satellite image, image compression, Normalized Gaussian distributive Ricker wavelet transformation, Fractal contraction mapping, iterated function system, Hutchinson Operator, Fractal decompression algorithm

1. INTRODUCTION

With the expensive growth of information technology, more multimedia information such as text, images, video, and audiocreates great challenges to storage and communication. Therefore, the data compression method is extensively applied in the process of data transmission, storage, and communication. Among this generated information, the number of images is much bigger attention than other types of data. But the image includes a lot of redundant information such as some noise redundancy and visual redundancy, etc. Therefore, Image compression is the process of eliminating or removing theredundancy in image representation. Image compression is the process to reduce the size of digital image files while maintaining quality.

Image compressionis partitioned into two types such as lossy and lossless. In lossy compression, some parts of the original image will be lost after compression. The losslesscompression remains similar to the original image after decompression. Lossless imagecompression is mainly used in some real-time applications such as medicalimaging, military communication, remote sensing applications, etc. The Lossycompression discards some non-redundant information in the input image to provide abetter compression ratio.Conventionally, large numbers of lossy and lossless image compression methods have been developed for the assessment of reconstructed imagequality.

An improved lossless image compression algorithm was introduced in [1] by using integer wavelet transform (IWT) and Huffman coding.The designed algorithm minimizes the compressible space by reducingthe redundancy of the original image. However, the complexity of the algorithm was not reduced to optimize the compression speed. A novel lossless compression encodingframework was developed in [2] for remote sensing images. The framework increases the compression ratio but the time consumption for image compression was not minimized.

An entropy minimization histogram mergence (EMHM) method was introduced in [3]to considerably minimize the number of grayscales and visible loss to image quality. But the higher compression ratio was not achieved. A novel lossy image compression method called singularvector sparse reconstruction (SVSR) was introduced in [4] for image compression and reconstruction quality. But it failed toimprove the reconstruction of the image.

Complex and novel Generative Adversarial BTC (GA-BTC) compression methods were developed in [5] toenhance the quality of block constructionsand reconstructions significantly. However, it failed to implementmoreimages by using multimedia resource compression strategies. A new symmetrical latticegenerating adversarial network (SLGAN) was developed in [6] forcompression of the remote sensing images. However, the method failed to evaluate a wider range of image datasets.

A discrete atomic transform was developed in [7] to effectively perform the compression. But it failed to analyze more images for performing the compression. Configurational entropy-based models were developed in [8] foran effective lossless compression ratio by using

Shannon's source codingtheorem. However, the prediction of the lossless compression ratio of multispectralimages was not considered.

A lossy hyperspectral image compression algorithm was designed in [9] based on theconcept of autoencoders to minimize the dimensions of the input image and produce a compressed image. But, it failed to improve the compression performance for hyperspectral images with less spatial correlation. A novelDNN-based image compression framework was developed in [10] by using the Laplacian pyramid to construct a multi-scaleimage representation. However, the designed framework was not efficient to minimize the compression time.

The major contribution of the proposed NGWT-FC technique is discussed in the below,

- A novelNGWT-FC technique is proposed to enhance the compression performance of satellite images.
- To improve the image compression ratio, iterated functional Fractal compression technique is introduced. The iterated functional system performs the contraction mapping between the domain and range blocks by using Hutchinson Operator. Finally, the best matching contracted domain block is identified for each range block through the affine transformation. As a result, the compressed image is obtained.
- To minimize the compression time, Normalized Gaussian distributive Ricker wavelet transformation is applied for the input satellite image decomposition to obtain different range blocks and domain blocks.
- The image decompression is performed based on the reverse process of compression to obtain the quality - improvedoriginal image. This helps to improve the peak signal-to-noise ratio.
- Finally, a number of qualitative and quantitative tests are performed using the proposed NGWT-FC and existing compression algorithms along with different performance metrics.

1.1 Paper outline

Rest of the paper is organized as five different sections. Section 2 deals with related literature survey of relevant works. Section 3 discuss about methodology of proposed NGWT-FC. It is followed Section 4 with description of Dataset and Experimental setup. In Section 5, quantitative analysis is made with four performance metrics. Conclusion of the Paper is discussed in Section 6.

2. RELATED WORKS

An Enhanced Multivariance Products Representation (EMPR) was introduced in [11] for lossy hyperspectral image compression. However, the designed method failed to effectively minimize the performance of space complexity after the image compression. An extended hybrid image compression method was developed in [12] based on soft-to-hard quantification.But it failed to improve the performance of the hybrid image compression to process the compact images.

A new variable-rate image compression framework was developed in [13]. But the designed framework was not efficient to improve the performance in terms of peak signal-to-noise ratio. A Context-based Convolutional Network (CCN) was developed in [14] for well-organized entropy modeling to improve image compression. But, it failed to solve various vision tasks such as image restoration and image quality assessment.

A deep Multi-Stage Representation-based Image Compression (MSRIC) technique was introduced in [15]. The designed MSRIC technique failed to investigate more images with lesser complexity. A compressive sensing paradigm was developed in [16] for image compression and reconstruction. Though the model improves compression ratio and peak signal-to-noise ratio, the analysis of adding noise to the input images and varying the reconstruction matrix was not performed. A hybrid coding framework was developed in [17] that integrate entropy coding, and deep learning for image compression. But, it fails significantly improve the performance of the compression scheme.

A Low-dimensional Visual Representation Convolution Neural Network (LVR-CNN) was developed in [18] for efficient post-transform-based image compression. Though the method increases the peak-signal-noise-ratio the performance of time consumption for efficient compression was not reduced. A new Sparse Flow Adversarial Model (SFAM) was introduced in [19] for image compression using a stable mapping between image distributions. But it failed to handle the lossless image compression. A novel F-transform was developed in [20] for the hybrid image compression and decompression process. However, it failed to decrease the execution time.

3. METHODOLOGY

The satellite image compression technique plays a vital role in both storage management systems and transmission. Image compression technique comprises two important processes namely compression and decompression. The compression process performs the operation of discarding information, whereas the decompression process is to recover lost information. In order to construct the decompressed image more similar to the original image, the classic image-processing techniques using two strategies such as lossy and lossless compression. However, its lack provides a higher accuracy rate in image recovering tasks. In order to improve the quality of image reconstruction, a novel technique called Normalized Gaussian Distributive Ricker Wavelet (NGDRW) is introduced for concentrating on improving image quality with higher compression ratio as well as decompression strategies.

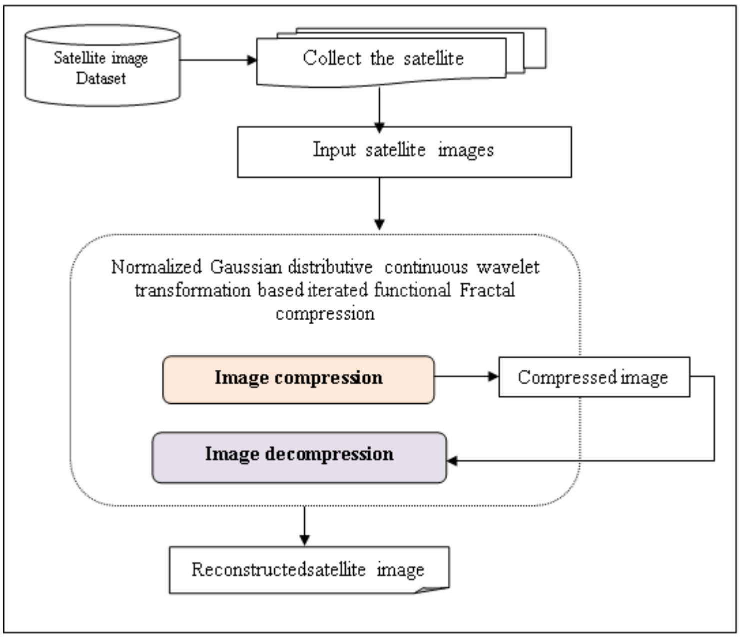

Figure 1 Architecture of the proposed NGWT-FC technique

Figure 1 demonstrates an architecture diagram of the proposed NGWT-FC technique to obtain the quality-improved reconstructed image. First, the number of satellite images $Si_1, Si_2, Si_3, \dots Si_n$ are collected from the input database 'DB'. After that, image compression is performed to minimize the storage complexity. First, the Normalized Gaussian distributive Ricker wavelet transform is applied for decomposing the satellite input image into two parts such as domain block and range blocks. The entire size of the input image is said to be a domain block. The size of images gets reduced through the downsampling is called range blocks. The decomposition is the process of separating a given input satellite image through downsampling and obtaining the different sub-blocks that are used for various applications in the fields of computer graphics and image processing. The main advantage of Ricker wavelet transform is,it provides simultaneous localization in both times as well as frequency domains. The second main advantage of wavelets is that computationally very fast and also separates the fine details in an image.

After the image decomposition, the Fractile contraction mapping between the domain block and range blocks is carried out using Iterated Function System (IFS).Iterated function system is a method of creating the fractals using self-similarity using the Hutchinson Operator by continuously mapping the pixels from the range block to the domain block. A fractal is a geometric shape including a detailed structure and each part of the shape has asimilar geometric characters. The advantage of fractal image compressionis tostore the mathematical formulas interms of fractal rather than as bit maps. In addition, the proposed compression technique has the ability to scale images without distortion.

Then the encoding process is performed to find the best domain block for each current range block through the transformation. By applying an affine transformation of domain block, the linear combination of different operations is performed such as translation, rotation, and scaling. Finally, the best domain block along with its mathematical data such as scaling and offset coefficient are saved into the fractal codes. In this way, a compressed image is obtained.

After that, the Fractal decompression process is performed as a reverse process of compression that converts the compressed image into the reconstructed image. Based on image compression, an efficient image quality enhancement is obtained. The brief discussion and mathematical formulation of the NGWT-FC technique aregiven below.

3.1 Normalized Gaussian distributive Ricker wavelet transform-based Fractal image compression

Image compression is the process of minimizing the problem of reducing the amount of storage space required to represent a digital image. It is a process intended to provide a compact representation of an image, thereby increasing the image quality. Therefore, the proposed NGWT-FC technique uses Fractal image compression for digital image quality enhancement. Fractal image compression is a lossy compression in which the original image is perfectly reconstructed from the compressed image. These are also called noiseless since they did not add noise to the reconstructed image. It is also used as a wavelet-based decomposition technique to minimize time complexity. Lossy compression is mainly used to compress the multimedia data such as audio, video, and images. The different process of Image compression using Normalized Gaussian distributive Ricker wavelet transform based Fractal image compressionis given below.

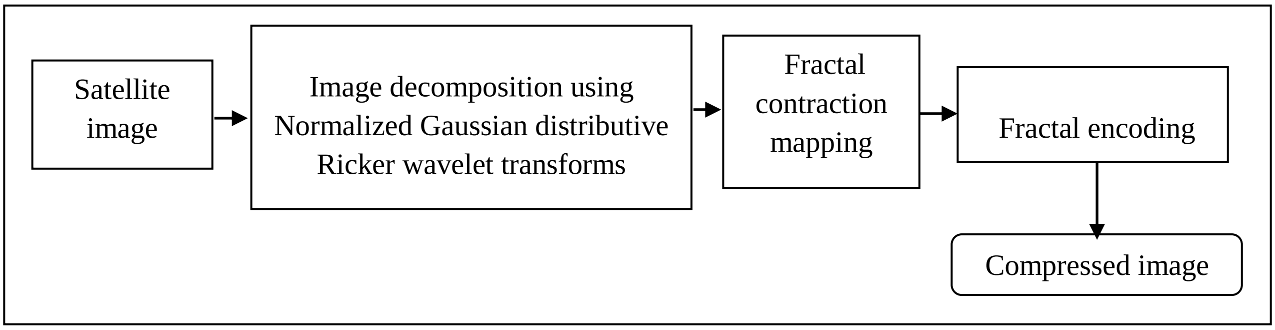

Figure 2 Normalized Gaussian distributive Ricker wavelet transform-based Fractal image compression

Figure 2 illustrates the block diagram of the image compression using Normalized Gaussian distributive Ricker wavelet transform-based Fractal compression. First, the satellite image is taken from the dataset. Then the image decomposition process is performed to obtain the range blocks and the domain blocks with help oftheNormalized Gaussian distributive Ricker wavelet transform. After that, the Fractal contraction mapping is performed between the range blocks and the domain blocks with help of the Hutchinson operator. Finally, the Fractal encoding process is performed to obtain the constructed image.

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3.1.1 Normalized Gaussian distributive Ricker wavelet transforms

Normalized Gaussian distributive Ricker wavelet transform is applied to processes the input image at various scales or resolutions. The proposed wavelet transform is used to partition the input satellite image into the domain blocks at every scale. This process continues, partitioning the subsection of the blocks into further smaller subsections in the same way.

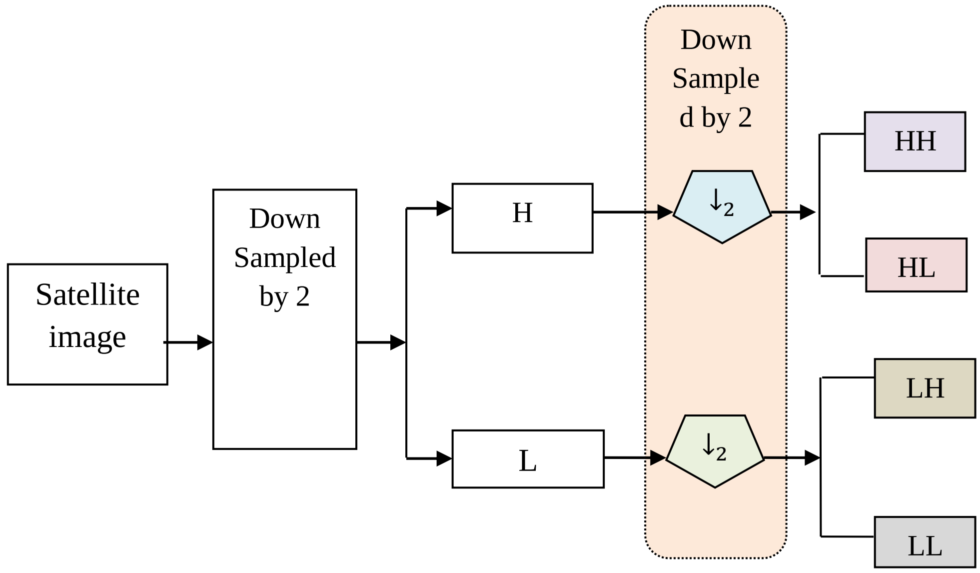


Figure 3 Normalized Gaussian distributive Ricker wavelet transforms based on image decomposition

Figure 3 illustrates the block diagram of the image decomposition based on the Normalized Gaussian distributive Ricker wavelet transform. In the first level forward transformation, Normalized Gaussian distributive Ricker wavelets transform is applied in both horizontal and vertical directions of the image. Then the input image is decomposed into two levels by applying the down sampling as low (L) and high(H). For the next successive levels, downsampling (i.e.$\downarrow_2$) is performed and the output of each level generates four sub-blocks namelyHH, LH, HL, LL. A similar process is performed again on the sub-band to generate the next decomposition level. Therefore, the transformation is performed as given below,

$$\varphi_t = \frac{2}{\sqrt{3\vartheta}\pi^{1/4}}\left(1-\left(\frac{t}{\vartheta}\right)^2\right)\exp\left(-\frac{1}{2\vartheta^2}t^2\right) \quad (1)$$

Where, above (1) is used for the normalized derivative of a Gaussian function. From (1),$\varphi_t$denotes a transformation output that decomposes the input image at a time ‘t’, ϑ indicates a deviation,

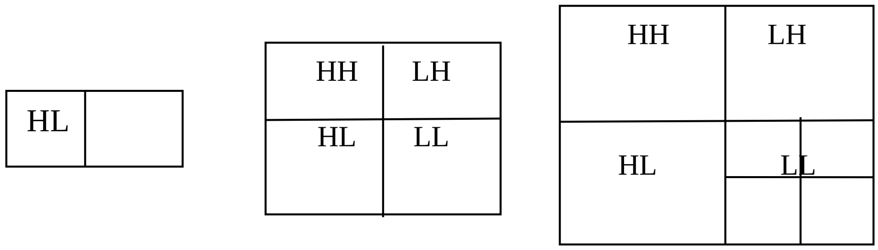


Figure 4(a) First-level Decomposition (b) Second level decomposition (c) Third level decomposition

Figure 4 (a), (b), and (c) shows the decomposition level of theimagesbased on the low (L) and high-frequency components. Figure 4(a) indicates the first level decomposition to obtain two sub-blocks. Figure 4(b) indicates a second-level decomposition to obtain four sub-blocks. Figure 4(c) indicates a third level to obtain eight sub-blocks. The size of the input image is said to be a domain block. The size of images gets reduced through the down sampling is called range blocks.

3.1.2 Fractal contractions mapping

After the image decomposition, each range block is matched with a domain block using Fractal contractions mapping as shown infigure 5.

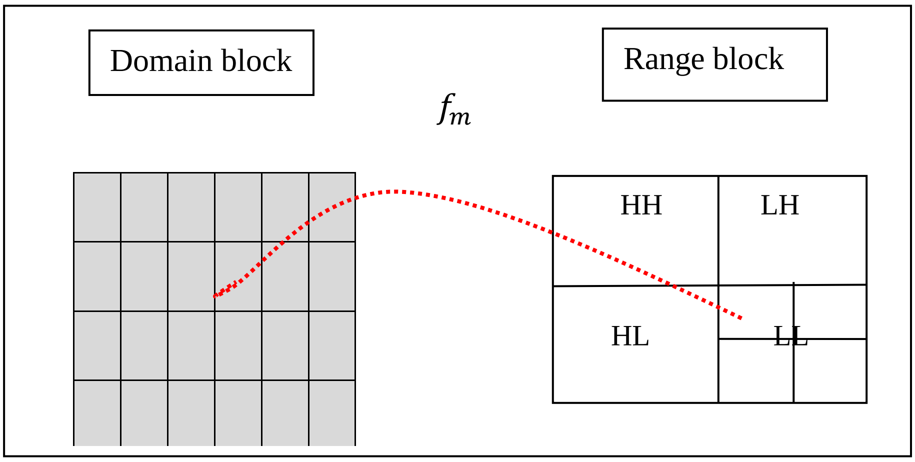


Figure 5 Fractal contractions mapping

During the fractal encoding process, Fractal mapping between the range block and domain block is described mathematically as an Iterated Function System (IFS). An IFS is a set of contraction mappings between the range block and domain block. Let us consider the pixels'p_r' in the range block with the position (x, y) and the pixels'p_d' in the domain block with the position(m, n). The contraction mapping is performed as given below

$$f_m: b_r(x, y) \to b_d\ (m, n)(2)$$

Where, $f_m$denotes a contraction mapping from range block 'b_r' to domain block 'b_d'. The Iterated Function System continuously maps the pixels from the range block to the domain block. Therefore, the distance relationship between the before and after mapping is given below

$$D_a[f(x), f(y)] \leq Q\,[D_b(x, y)] \qquad (3)$$

Where, D_a denotes a distance after mapping, D_b denotes a distance of before mapping, Q denotes a constant range from 0 to 1,(x, y)denotes a point in a two-dimensional plane, $f(x), f(y)$ denotes a mapped point in two-dimensional plane.

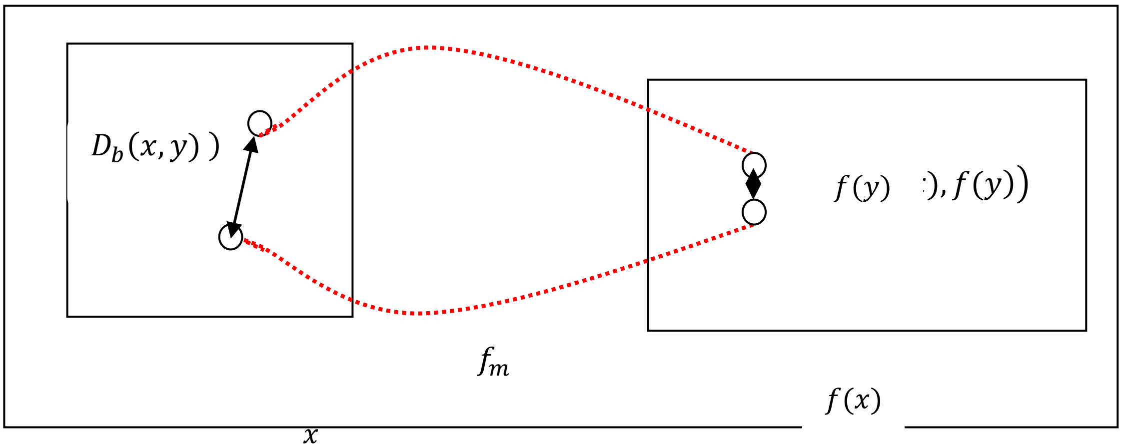


Figure 6 Contraction Mapping

According to these mapping functions, the collective set of contractions is called as Hutchinson operator.

$$h = \sum_{i=1}^{n} f_{mi}\,(s) \quad (4)$$

Where, h indicates a Hutchinson operator, f_{mi} denotes a collective set of contractions function over a subsets 's'.

3.1.3Fractal encoding

Finally, the Fractal encoding process is performed to obtain the reconstructed image. In order to minimize the mapping error, each contracted domain block is transformed as follows,

$$T_{d_b} = \alpha d_b + \beta \quad (5)$$

Where, T_{d_b} denotes a transformed domain block 'd_b', α, β are scaling coefficient and offset coefficient,offset coefficient is the information about the pixels of the image $\beta \epsilon\,[-255,255]$. Here, the affine transformation is applied to a domain blockand the different operations is performed such as translation, rotation, and scaling. For each range blockb_r, the best matching domain block after the transformation is obtained by minimizing the distancefunction,

$$E = \arg\min \left\| b_r(x, y) - T_{d_b}(m, n) \right\| \quad (6)$$

Where, 'E' denotes anfunction to minimize the distance, $arg\,min$ denotes an argument of a minimum function to minimize the distance between range block' $b_r(x, y)$' and transformed domain block' $T_{d_b}(m, n)$'. With the least squares method, α and $\beta$are computed as follows,

$$\alpha = \frac{n^2 \sum(b_d\,(m,n))(b_r(x,y)) - ((\sum b_d\,(m,n)) * (\sum b_r(x,y)))}{n^2 \sum(b_d\,(m,n))^2 - (\sum b_d\,(m,n))^2} \quad (7)$$

$$\beta = \frac{(\sum b_d\,(m,n))^2 - (\sum b_r(x,y))^2}{\mathrm{n}^2 \sum(b_d\,(m,n))^2 - (\sum b_d\,(m,n))^2} \quad (8)$$

Where 'n'indicates the size of the range block,' $b_d\,(m,n)$denotes a domain block with the position(m,n).$b_r(x,y)$ denotes a range block with the position (x,y).The transformed domain block is found to be the best approximation for the current range block. Therefore, the transformation of input satellite image parameters such as coordinates of best domain block along with itsα, $\beta$is saved into the file as the fractal code.

$$Y = b_{d\,(best)}(m,n) \rightarrow F_{code} \quad (9)$$

Where, Y denotes an output of the compressed image, $b_{d\,(best)}(m,n)$ denotes the best domain block for each range block,F_{code} denotes a fractal code. In this way, a compressed image is obtained with minimum time. The algorithmic process of image compression is given below

Algorithm 1: Normalized Gaussian distributive Ricker wavelet transform-based Fractal image compression
Input: database, Satellite images $Si_1, Si_2, Si_3, \ldots Si_n$
Begin **1.** **Number of** Satellite images $Si_1, Si_2, Si_3, \ldots Si_n$**taken as** input \\ **Image compression** **2.** **For each** Satellite imageSi_i, **3.** Apply Normalized Gaussian distributive Ricker wavelet transform 'φ_t' **4.** Decompose the image into domain '$b_d\,(m,n)$' and range blocks $b_r(x,y)$ **5.** **end for** **6.** Perform Fractal contractions mapping **'**f_m**'** **7.** **for each** range block **8.** Apply affine transform to contracted domain block 'T_{d_b}' **9.** **Measure** scaling coefficient and offset coefficient 'α, β' **10.** Find minimum distance between range block '$b_r(x,y)$' and transformed domain block 'T_{d_b}' **11.** **End for** **12.** **Obtain the** best matching domain block 'Y' **13.** **end for** **14.** Save the mapping information as fractal code **15.** **Return (**compressed image) **End**

As shown in algorithm 1, normalized Gaussian distributive Ricker wavelet transform-based fractal image compression consists of three steps as follows. Initially, the satellite image is taken from the data set as input and applied to a Normalized Gaussian distributive Ricker wavelet transformfor decomposing the image into the domain and range blocks. Next, Fractal contraction mapping is applied between the range blocks and domain blocks. Finally, the Fractal encoding process is performed. In the encoding process, apply the affine transformation to the contracted domain block. For each range block, the best matching domain block is obtained by minimizing the distance between the range block and the transformed domain block. Finally, the compressed image is obtained to further decrease the overall size of the satellite image. With the support of the above algorithmic process, the proposedtechnique compresses the satellite images with a higher compression ratio. This also helps for reducing the space and time complexity of image compression effectively.

3.2 Fractal image decompression

In the proposedtechnique, image decompression is performed in order to obtain the reconstructed satellite image for quality analysis. Image decompression is the reverse process of image compression.

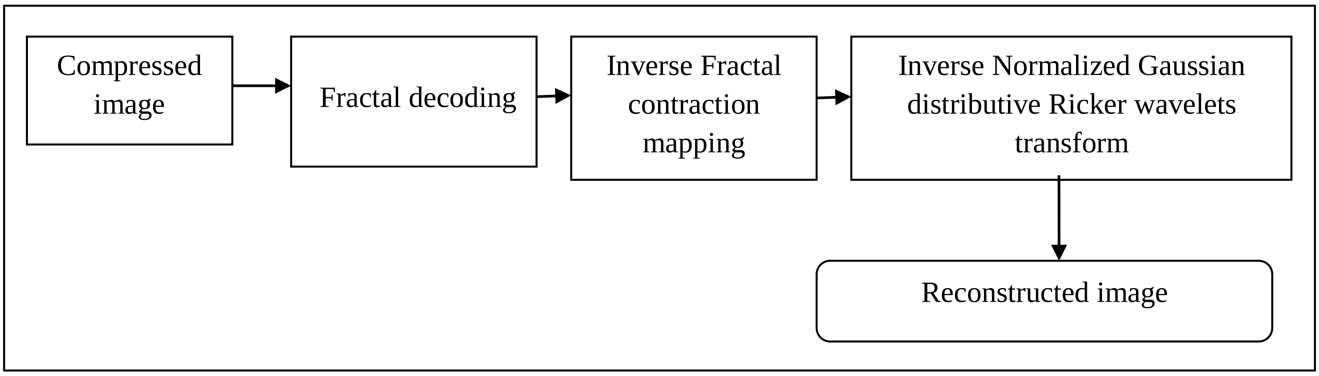


Figure 7 Block diagram of Fractal Image Decompression

Figure 7 illustrates the block diagram of the image decompression process. First, the compressed satellite image is taken as input. Then the Fractal decoding process is performed by finding the best matching contracted domain block. The best matching results are obtained by minimizing the distance between the range block and the transformed domain block. Following this, the inverse process of Fractal contraction mapping is performed. Finally, the Inverse Normalized Gaussian distributive Ricker wavelets transform is applied to obtain the reconstructed original image. In this way, the Fractal image decompression is obtained. The algorithmic process of Image Decompression is shown below,

Algorithm 2: Normalized Gaussian distributive Ricker wavelet transform-based Fractal image decompression
Input: database, compressed satellite image $Ci_1, Ci_2, Ci_3, \ldots Ci_n$
Begin **1.** Compressed image $Ci_1, Ci_2, Ci_3, \ldots Ci_n$is **taken as** input \\ **Image decompression** **2.** **For each** Compressed image Ci_i, **3.** **Perform decoding** to convert an encoded format back into the original image parameters

4.	Apply inverse transform to contracted domain block 'T_{d_b}'
5.	**end for**
6.	Apply inverse Normalized Gaussian distributive Ricker wavelet transform
7.	Merge the domain block '$b_d\ (m,n)$' and range blocks $b_r(x,y)$
8.	Obtain thereconstructed image
9.	**Return** quality improvedreconstructed image
10.	
End	

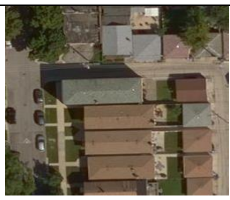
Algorithm 2 describes the process of Normalized Gaussian distributive Ricker wavelet transform-based Fractal image decompression. The algorithm initially takes the input as a compressed satellite image. Then it performs a decoding process for converting an encoded image format back into the original range and domain blocks by applying the inverse transformation of the contracted domain block. After that, the inverse Normalized Gaussian distributive Ricker wavelet is applied to the decoded image to merge the domain and range blocks. As a result, the reconstructed quality improved satellite image is obtained.

4. EXPERIMENTAL SETTINGS

In this section, experimental assessment of the NGWT-FCtechnique and the namely lossless compression encoding framework [1] and improved lossless image compression algorithm [2] isperformed using MATLAB coding for compression with the number of satellite images collected from the https://www.kaggle.com/datasets/sohelranaccselab/satellite-data. The RSI-CB image database is a larger-scale benchmark database than any of the other databases. The database consists of 24,767 images distributed in 35 categories such as airplane, airport_runway, artificial_grassland,avenue, bare_land, bridge, city_building, coast_line, container, crossroads, dam, desert, dry_farm, forest, green_farmland, highway, hirst, lakeshore, mangrove, marina, mountain, parking lot, pipeline, residents, river, river_protection_forest, sandbeach, sapling, sea, shrubwod, snow_mountain, sparse_forest, storage_room, stream and town For the experimental consideration, 1000 to 10000 images are considered with various sizes to perform the statistical evaluation with various input parameters.

4.1 Qualitative Performance Analyses

The qualitative analysis of the NGWT-FCtechnique is discussed with various processes.

	Processes	Output results
1.	Input satellite image	

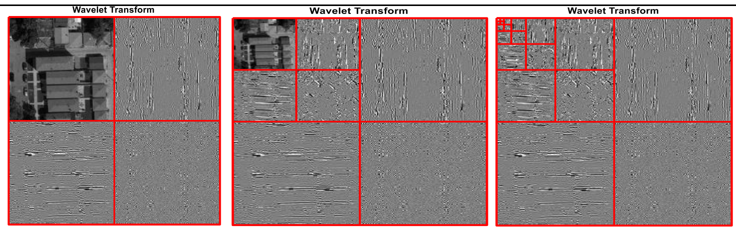
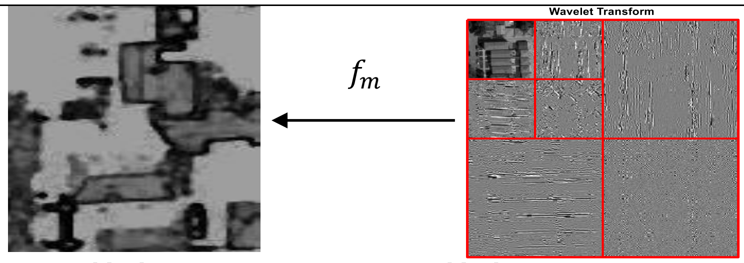
2.	Normalized Gaussian distributive Ricker wavelet transformation	
3.	Fractal Contraction Mapping	 Domain block Range block
4.	Compressed image	Compressed Image 
5.	Decompressed Image	Decompressed Image 

Figure 8Qualitative Results of NGWT-FC Technique

EVALUATION PARAMETERS

There are different performances metrics are used to analyze the performance of the NGWT-FCtechnique over the existing methods. The definition of the metrics are given below,

1. **Peak Signal-to-Noise Ratio**: it is used to compute the compressing capacity of the algorithms.The peak signal-to-noise ratio is measuredbased on mean square error. The mean square error is measured as the difference between the number of the original image and the number of images correctly reconstructed.

$$ratio_{psn} = 10 * \left[log_{10}\left(\frac{255^2}{\frac{1}{n}\sum(TNSI - NSICR)^2}\right)\right] \qquad (11)$$

Where 'n denotes the number of satellite images, $TNSI$ denotes the total number of satellite images, $NSICC$ denotes the number of images correctly reconstructed. From (11), $ratio_{psn}$indicates a peak signal-to-noise ratio. The assessment of peak signal-to-noise ratio is measured in the unit of decibels (dB).

2. **Compression ratio:** It is defined as the ratio of the original image size to the compressed image size. The compression ratio is mathematically formulated as follows,

$$Ratio_{comp} = \left[\frac{original\ image\ (KB)}{compressed\ image\ (KB)}\right] (12)$$

Where, $Ratio_{comp}$ denotes a compression ratio. Higher the compression ratio, the technique is more efficient.

3. **Compression time:** It is defined as the amount of time taken by the algorithm to compress the given input images. The formula for calculating the compression time is expressed as follows,

$$CT = n * T \langle cp\ (Si)\rangle \ (13)$$

From (13),CT indicates a Compression time, 'n' indicates a number of images, T denotes the time taken by the algorithm to compress the satellite image $i.e\ T\ \langle cp\ (Si)\rangle$. The Compression time is measured in milliseconds (ms).

4. **Space complexity:** It is defined as the amount of storage space taken by the algorithm to store the given input images after the compression. The formula for calculating the space complexity is expressed as follows

$$sp_{com} = n * Mem\ \langle cp\ (Si)\rangle \ (14)$$

From (14),sp_{com} indicates a space complexity, 'n' indicates the number of satellite images, Mem denotes the time taken by the algorithm to compress the satellite image $i.e\ T\ \langle cp\ (Si)\rangle$. The Compression time is measured in milliseconds (ms).

5.1 Quantitative Performance analysis

In this section, performance discussion of the various metrics with three different techniques namely NGWT-FCtechnique and the two state-of-the-art methods namely Lossless compression encoding framework [1] and Improved lossless image compression algorithm [2] are discussed. Initially, the peak signal-to-noise ratio is evaluated with various sizes of the input satellite images illustrated in table I.

Table 1 Comparison of Peak Signal to Noise Ratio

Satellite images (Numbers)	Peak SignaltoNoise Ratio (dB)		
	NGWT-FC	Lossless compression encoding framework	Improved lossless image compression algorithm

1000	58.13	53.07	51.31
2000	57.71	52.56	51.05
3000	56.08	52.33	50.88
4000	54.15	51.69	50.57
5000	53.81	50.80	50.20
6000	53.50	50.64	50.06
7000	52.69	50.34	49.80
8000	51.59	50.27	49.67
9000	51.31	50.06	49.61
10000	51.22	49.87	49.55

Table 1 provides the performance results of peak signal-to-noise ratio with the number of satellite images 1000, 2000… 10000 collected from the database. The peak signal-to-noise ratio is measured using three different methods namely NGWT-FC, lossless compression encoding framework [1], and improved lossless image compression algorithm [2].

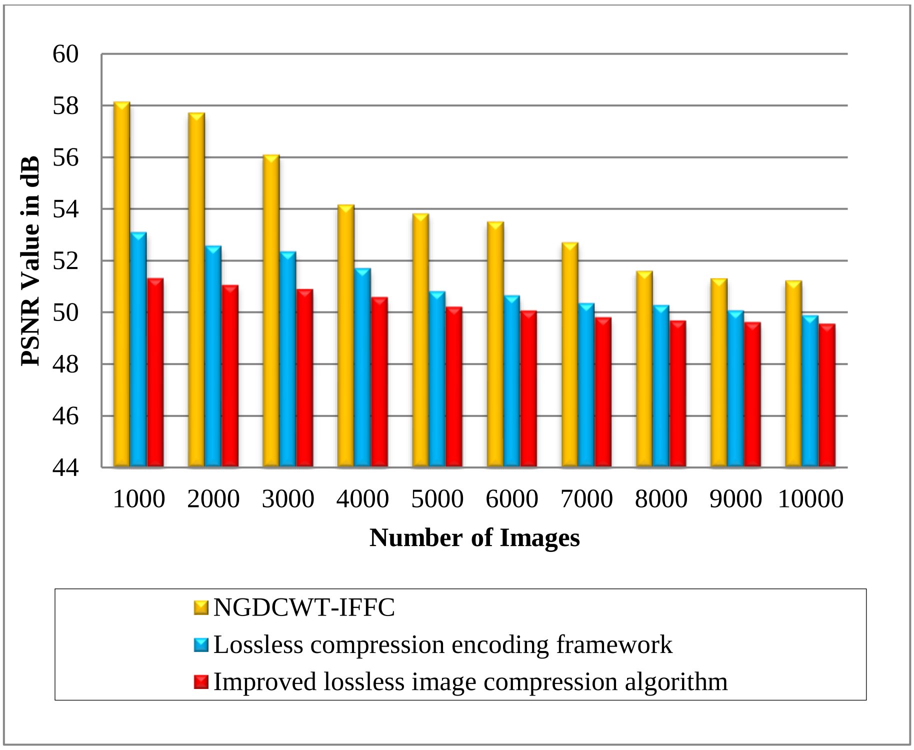


Figure 9 comparative results of Peak Signal-to-Noise Ratio

The observed results indicate that the performance of the peak signal-to-noise ratio is improved using the NGWT-FC technique when compared to existing methods. This was proved through statistical estimation. Let us consider 1000 satellite images collected from the database. The peak signal-to-noise ratio between the original image and the reconstructed image is calculated by using NGWT-FC. The observed performance results of NGWT-FC are58.13 dB and the performance of peak signal-to-noise ratio using existing [1] [2] are 53.07dB and 51.31 dB respectively. Similarly, different numbers of images are taken as input for conducting the experiments. The observed results of NGWT-FC are compared to the results of existing methods. Finally, the averages of ten comparison results are used to show the performance improvement of the NGWT-FC technique. The average results indicate that the peak signal-to-noise ratio of NGWT-FC is improved by 6% when compared to [1] and 7% when compared to [2] respectively.

Figure 9 illustrates the graphical outcomes of peak signal-to-noise ratio versus various numbers of satellite images. The number of images taken onthehorizontal axis and the performance outcomes of the peak signal-to-noise ratio are obtained onthevertical axis. The graphical representation noticed that the proposed NGWT-FC technique achieves improved results of peak signal-to-noise ratio than the other two existing compression methods. This is because of applying the iterated functional Fractal image compression in which the original satellite image is correctly reconstructed from the compressed image. These are also called noiseless since they did not add noise to the reconstructed image. Therefore, the output of reconstructed image quality level gets improved.

Table 2 Comparison of Compression Ratio

Satellite images	Image Sizes (KB)	Compression Ratio		
		NGWT-FC	Lossless compression encoding framework	Improved lossless image compression algorithm
Image 1	179	1.154	1.052	1.022
Image 2	185	1.233	1.063	1.033
Image 3	186	1.248	1.075	1.050
Image 4	187	1.263	1.087	1.062
Image 5	188	1.278	1.105	1.074
Image 6	189	1.294	1.118	1.092
Image 7	190	1.310	1.120	1.104
Image 8	191	1.345	1.133	1.116
Image 9	192	1.422	1.158	1.129
Image 10	193	1.451	1.200	1.142

Table 2 provides the performance results of compression ratio with respect to the number of satellite images collected from the database. In order to conduct the experiment, the sizes of different images are taken from the database. Among three different compression methods, NGWT-FC achieved a higher compression ratio than the conventional methods. Let us consider, that the input satellite image size is179KB. Therefore, the performance of compression ratio using three methods namely NGWT-FC, lossless compression encoding framework [1], and improved lossless image compression algorithm [2] are 1.154, 1.052, and 1.022 respectively. Similarly, different outcomes are observed for each method with respect to different sizes of the input images. The average of ten comparison outputs results

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indicates that the overall compression ratio of NGWT-FC is significantly increased by 17% when compared to [1] and 20% when compared to [2].

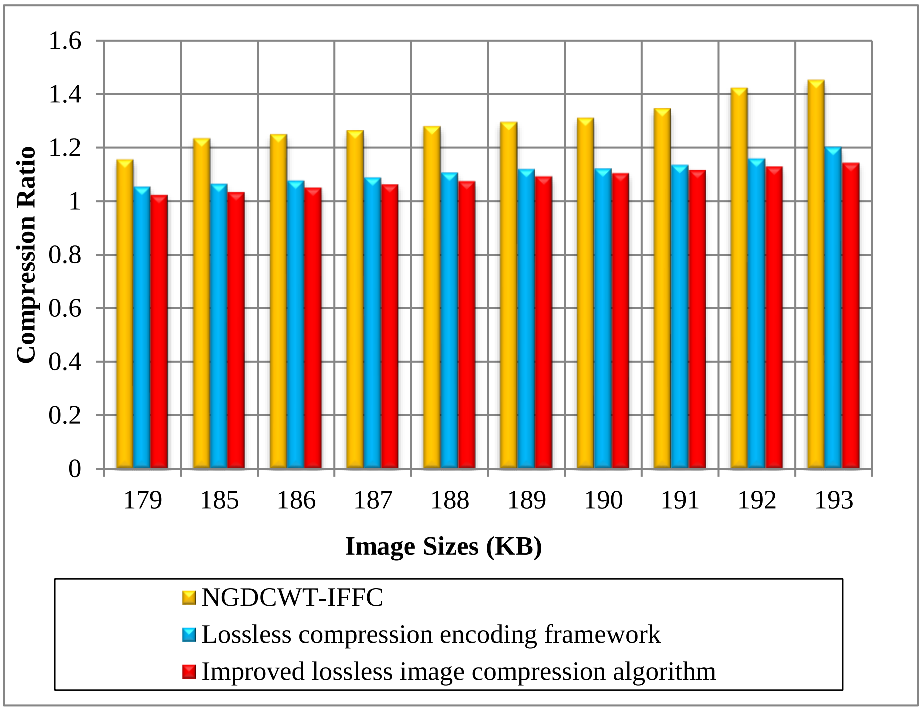

Figure 10 graphical representation of compression ratio

Figure 10 shows the compression ratio during image compression based on the size of the image in the database. Compared to the existing compression techniques, the proposed NGWT-FC technique improves the compression ratio even with the increase in the size of images in the dataset. In the proposed NGWT-FC technique, Normalized Gaussian distributive Ricker wavelet transformation is performed where the mapping between domain block and range blocks in the fractal compression. After that, the best matching transformed domain block is identified for each range block and hence the improved compression ratio is obtained with different image sizes.

Table 3 comparison of compression time

Satellite images (number	compression time (ms)		
	NGWT-FC	Lossless compression encoding framework	Improved lossless image compression algorithm
1000	125	134	145
2000	220	256	284
3000	270	330	390
4000	320	360	440
5000	350	400	475
6000	393	450	510
7000	448	490	560

8000	528	576	616
9000	585	621	675
10000	620	670	700

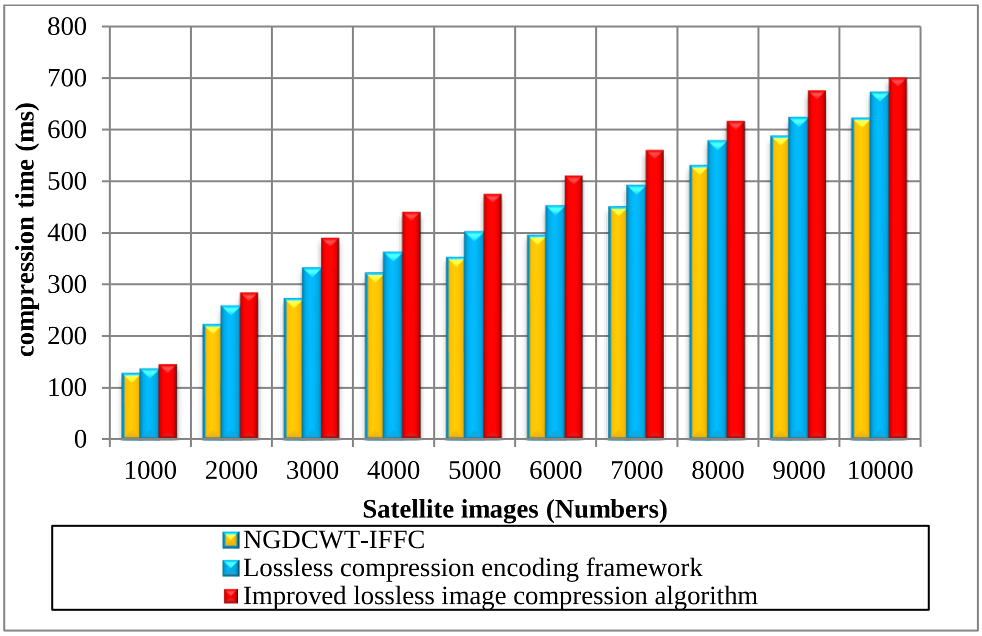

Figure 11 graphical representation of compression

Table 3 and figure 11 present the overall performance analysis of compression time with respect to a number of satellite images taken from the database. As shown in graph 11, the compression time of three different methods namely NGWT-FC, lossless compression encoding framework [1], and improved lossless image compression algorithm [2] is improved. But, the performance of compression time using NGWT-FC is relatively lesser than the other two existing compression methods. As an experiment is conducted with '1000' input satellite images, the compression time was found to be '125ms' using NGWT-FC,'134ms' using [1], and 145ms' using [2]. However, the overall performance analysis proposed technique is compared to existing methods. The average comparison results indicate that the compression time using NGWT-FC is found to be minimized by 11% and 20% when compared to existing [1] [2] respectively. This is because of applying the Normalized Gaussian distributive Ricker wavelet transform to decompose the input satellite image into domain and range blocks for accurate image compression with minimum time.

Table 4 Comparison of Space complexity

Satellite images (numbers)	Space complexity (MB)		
	NGWT-FC	Lossless compression encoding framework	Improved lossless image compression algorithm
1000	640	800	920
2000	880	960	1100

3000	930	1050	1350
4000	1000	1120	1320
5000	1150	1250	1400
6000	1260	1320	1500
7000	1400	1540	1645
8000	1520	1600	1760
9000	1620	1710	1800
10000	1750	1860	1950

Table 4 and figure 12 given above illustrate the overall performance analysis of space complexity of three different methods namely NGWT-FC, lossless compression encoding framework [1], and improved lossless image compression algorithm [2].

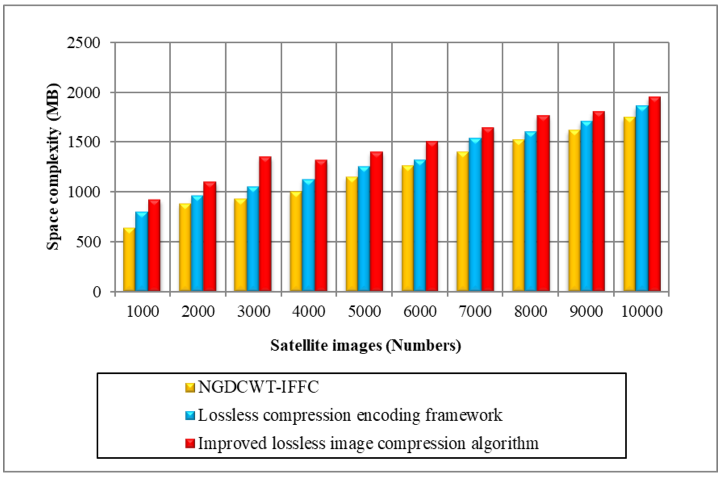

Figure 12 graphical representation of space complexity

The space complexity of the three compression algorithms is measured with respect to the number of satellite images taken from the database. As shown in the results, the space consumption of all three methods gets increases while increasing the number of input images. But comparatively, the space complexity of the NGWT-FC technique is found to be minimized. For each compression method, ten different results are observed with respect to a number of images. The overall observed results of the NGWT-FC technique are compared to existing methods. Finally, the average of ten results indicates that the performance analysis of space complexity using the NGWT-FC technique is minimized by 9% and 19% when compared to existing compression techniques [1] [2] respectively. This is due to the NGWT-FC technique accurately compressing the input image with the help of iterated functional Fractal compression method.

6. CONCLUSION

In this paper, a novel compression technique called NGWT-FC is introduced for compressing thesatellite images. In the proposed NGWT-FC technique, the compressionoperation consists of image decomposition, mapping, and encoding operations.During decomposition, the

NGWT-FC images are decomposed to obtain a range and domain blocks. Thissmoothed image is then down-sampled to remove redundancy. After the image decomposition, the Fractile contraction mapping between domain and range blocks is carried out using Iterated Function System (IFS). Finally, the encoding process is executed to convert the image into mathematical data termed fractal codes. In this way, a compressed image is obtained. After the compression, image decompression is performed to convert the encoded image into readable form with higher quality. The comprehensive experimental evaluation is carried out with a satellite images dataset. The quantitatively analyzed results indicate that the NGWT-FC has received improved performance in terms of achieving higher peak signal-to-noise ratio, compression ratio and lesser time consumption, and space complexity when compared to existing compression techniques.

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