



Available online at www.qu.edu.iq/journalcm

JOURNAL OF AL-QADISIYAH FOR COMPUTER SCIENCE AND MATHEMATICS

ISSN:2521-3504(online) ISSN:2074-0204(print)



Semi-lossless Fractal MRI Image Compression Based on Fixed length Technique

Baidaa A. Al-Salamee¹, Dhiah Al-Shammary¹

¹College of Computer Science and Information Technology, University of Al-Qadisiyah, Iraq,

baidaalsalamee@gmail.com , d.alshammary@qu.edu.iq

ARTICLE INFO

Article history:

Received: 23 /08/2021

Revised form: 05 /09/2021

Accepted : 20 /09/2021

Available online: 13 /10/2021

Keywords : Medical; Image; Compression; CT; MRI; Lossless

ABSTRACT

Medical image compression plays an essential role to handle large amounts of data for communication and storage purposes. Fractal image compression is a potential lossy compression models with a resulting image that loses some of its information. However, health data communication usually cannot afford any lose for patients visual information. This paper proposes a new high efficiency semi-lossless fractal image compression method (SLFIC) based on fractal theory and fixed length technique. Technically, the resultant lossy fractals compressed image is analyzed and error in comparison with the original image is detected. Then, Fixed-length is developed to compress the detected errors and attached to the compressed image. In practice, a potential performance by the new developed model has been obtained in comparison with two other lossless models: (Lion optimization algorithm (LOA) and Lempel Ziv Markov chain Algorithm (LZMA) with Linde-Buzo-Gray (LBG) (L2-LBG)) and (Neural Network Radial Basis Function (NNRBF)). Moreover, a high quality that has been obtained by the proposed system based on Peak Signal to Noise Ratio (PSNR) and Compression Ratio (CR).

MSC. 41A25; 41A35; 41A36,,

DOI : <https://doi.org/10.29304/jqcm.2021.13.3.854>

1. Introduction

In healthcare systems the imaging process plays an important role nowadays especially after the amazing development that took place in the field of information technology [1].

*Corresponding author Zinah S. Abduljabbar

Email addresses: zinahsadeq@uomustansiriyah.edu.iq

Communicated by: Dr. Rana Jumaa Surayh aljanabi.

Medically, the imaging services are composed of different modalities such as MRI, CT and etc. [2]. This type of imaging provides high resolution digital images with rich details for the captured part of the patient's body, which greatly assists doctors in the diagnosis and treatment of the disease [3].

1.1 Motivation

medically, telemedicine applications have become widespread and widely used today [4]. These applications relied on different forms of data -image, video- which transmitted over the network and used in various applications [5]. The most popular types of images used for this purpose are CT and MRI [6]. These images distinguish technically by their high accuracy as a result of containing many details in order to avoid the doctor falling into an inaccurate diagnosis [7]. Consequently, telemedicine application facing some potential challenges such as storage problem and bandwidth of the network [8].

1.2 Proposed solutions

Image compression is a most popular technique used to minimize the size of digital images by compressing its data while striving to maintain image quality and accuracy [9]. In practice, there are two types of image compression techniques are lossy and lossless [10]. With lossy model the reconstructed image will lose some of its data, at variance lossless technique which keeps the original image as it without data loss. Fractal image compression considered one of common lossy image compression models [11]. In this paper we will produce a near lossless image compression based on fractal theory by computing error values (differences values between the original and reconstructed image).

1.3 Evaluation and analysis

In this paper the evaluation strategy was developed on the basis of testing the efficiency of the proposed system and the accuracy of the results obtained. As a result, PSNR (Peak Signal to Noise Ratio) and CR (Compression Ratio) have been used to compare their results with the obtained results of the proposed model to prove its efficiency. Samples with different sizes are selected to monitor the behavior of the proposed system and its results. Promising results were presented by the proposed model in terms of image resolution, as it scored high results with various sizes of large and small images.

1.4 Paper organization

The rest of this paper is organized as follows: section 2 shows the related works for some researchers. Fractal image compression is illustrated in section 3. Furthermore, fractal iterated function system is clarified in section 4. The proposed technique is described in section 5. Section 6 is composed of two subsections which illustrated results and analysis: (evaluation metrics) and (analysis and comparisons). Finally, the conclusion is showed in section 7.

2. Related Work

The main objective from lossless image compression technique is to maintain the details of the original image and prevent data loss or change, especially with images used for sensitive purpose that require high accuracy. There are many research studies that have sought to provide lossless image compression techniques and have achieved good results with regard to the accuracy of the resulting images. . Sujitha B et al [12] have addressed the problem of the big amount of information for remote sensing images used by intelligent devices for observation, gathering, communication and investigation of data (industrial internet of things). They have attempted to minimize communicating images size -represent a real obstacle for storage and transmission - with preserving high quality.

This article has proposed a deep learning method based on CNN (convolutional neural network) to compress remote sensing images. The encoding operation involved to use CNN in order to maintain the structural data through learning the compressed representation of the original images and then encode them by Lempel Ziv Markov chain algorithm. The decoding process has involved the inverse procedure of encoding to retrieve the original image attempting to get high reconstructed image quality.

Three main metrics: PSNR, CR and CF (compression factor) have been used for evaluating the efficiency of the proposed model (D-CNN). Furthermore, the obtained results have been compared with other models namely,

BTOT (Binary Tree and Optimized Truncation), JPEG, JPEG 2000. D-CNN has achieved CR about (0.08-0.12) while other models have achieved (0.11-0.19), (0.12-0.19), (0.48-0.78) for BTOT, JPEG and JPEG 2000 respectively. CF for D-CNN has been resulted (7.7-11.4). On the other hand, CF for other models have resulted in (5.1-8.8), (5-8), (1.3-2.07) for BTOT, JPEG and JPEG 2000 respectively. Finally, D-CNN has resulted in PSNR about (45-48) whereas other models have achieved about (45-47), (40-43), (45-47) for BTOT, JPEG and JPEG 2000 respectively.

Despite of high PSNR achieved in this paper, the authors did not mention models encoding/decoding time completely. This is a big weakness as the main target for this research is IoT which mainly require significant models in terms of performance.

With aim to reduce a large amount of remote sensing images udhakar llango, S. et al [13] have attempted to minimize the number of required bits to construct an image and decreasing their transfer size. This would facilitate the collection of image data on dangerous or inaccessible areas taking in to account the image quality. This paper has proposed an enhanced approach to 2D - dual tree -complex wavelet transform (2D-DT-CWT) with fuzzy interference (FIF) in order to avoid some significant limitations. Hybrid 2D-oriented biorthogonal wavelet transform (2D-BWT) with windowed all phase digital filter (WAPDF) based on discrete wavelet transform (DWT) have been applied in order to achieve robust compression. Images have been compressed using 2D-DWT and WAPDF to optimize transformation. The coefficients have been selected using FIF.

Wavelet significant coefficients have been encoded using CABAC (contextual - adaptive binary arithmetic coding) with LVQ (lattice vector quantization). With the aim to validate the proposed model efficiency, PSNR, CR and execution time have been computed. Furthermore, resultant metrics for 2D-DT-BDWT have been compared with other models named, JPEG 2000, 2D-OWT (2D-oriented wavelet transform), 2D-DT-CWT with fuzzy. 2D-DT-BDWT has resulted in CR about (4) while other models about (3.9,4,4) for JPEG 2000, 2D-OWT and 2D-DT-CWT respectively. Similarly, PSNR values have reached (38-40) for 2D-DT-BDWT. On the other hand, other models have less PSNR about (30-32), (33-37), (35-38) for JPEG 2000, 2D-OWT and 2D-DT-CWT respectively. Finally, resultant execution time was about (1.7 sec.-1.8 sec.) whereas other models have consumed about (3 sec., 2 sec., 1.8 sec.) JPEG 2000, 2D-OWT and 2D-DT-CWT respectively.

In fact, the proposed method results in this paper have shown high efficiency and robustness for remote sensing image compression. However, the obtained results have slightly improved in comparison with 2D-DT-CWT. Furthermore, this paper did not clarify the number of samples have been used in evaluation process to ensure of the validation tests are sufficient or insufficient.

Moreover, a novel lossless compression for SAR remote sensing images has been produced by Fan, C. et al [14]. They have discussed the problem of the large size of remote sensing images focusing on SAR (synthetic - aperture radar) which usually requires highly efficient devices able to store and transfer images. They have attempted to reduce large sizes with the capabilities to maintain image quality.

This paper has proposed a novel lossless compression based on processing separation of the outline of an image and their highly frequent portions. It aims to relatively increase neighbor pixel and therefore, the prediction accuracy has been optimized improving data compression efficiently. Outline image was down-sampled. Nonlocally centralized sparse representation method has been applied for pixel prediction based on the information of nonlocal similar region. Finally, down sampled image, high frequency and encoding parameter have been encoded to generate final bit stream. CR was the main evaluation metric in this paper. The proposed model achieved CR results have been compared with other models called: PNG, TIFF, CALIC and JPEG 2000. The resultant CR for the proposed model were about (1.7-7.9) while other models have reached (1.02-1.2), (1.04-1.17), (1.04-1.16), (1.01-1.42) for: PNG, TIFF, CALIC and JPEG 2000 respectively.

The proposed model has modest results in terms of CR even the compression approach is lossless. Moreover, PSNR metric and execution time were missing completely from this article and therefore, the efficiency of the model can never be judged.

3. Fractal Image Compression

The basic concept of the fractal is a segmented geometric shape which can be subdivided to several parts, each on is approximately similar the original shape [15]. The mathematical description has been formed for enormous and irregular shape of objects using fractal theory [15].

Technically, the basic definition for the fractal is structure form has been repeated [16]. The fundamental principle of fractals is self-similarity concept and is the main solution of many fractal applications [16]. Furthermore, the classification of fractals depends on their self-similarity [15]. One of the most lossy compression methods for digital image is fractal compression [16]. This method depends on fact that many parts of any image are similar and repeated [16].

4. Fractal Iterated Function System

A fractal is composed of union of multiple copies of itself, using a function (Iterated Function System (IFS)) each one being transformed [15]. Possibly, fractal is consisted of many overlapping mini copies of itself each one in turn is formed of copies of itself [15]. Therefore, for any specific object P, a Partitioned Iterated Function System (PIFS) has been found using fractal process based on fractal theory, $F = f_i : i = 1, \dots, k$ that are nonoverlapping tiles (commonly named Range block) of P, which each one of the tiles is created using a certain affine transformation f_i on a part of P [16].

$$f(P) = \cup_{i=1}^k f_i(d_i) \quad (1)$$

Where K represented the number of range blocks, d_i represented an arbitrary numeric part of the object P (named domain). The highest possible approximation of r_i has been given using each transformation of $f_i(d_i)$.

5. Proposed Semi-lossless Fractal Image Compression (SLFIC)

A new technique using fixed length encoding will be used to provide a compressed image based on fractal theory (lossy compression) with data loss almost non-existent. After completing compression process and obtaining the required information (Scale, Offset, Location) for all range blocks, decompression process will be executed on the resulting information and error catching will be detected to get the differences between the original information and the decoded information. The obtaining differences values will be encoded using fixed length technique and sending it with the other data in one encoding image file. fig 1 and 2 illustrate the main stages of the SLFIC system.

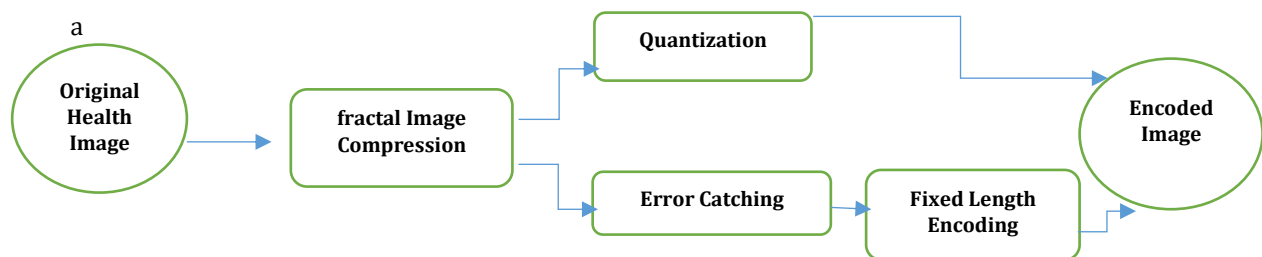


Fig. 1 -The Main Components Of SLFIC System (Encoding process)

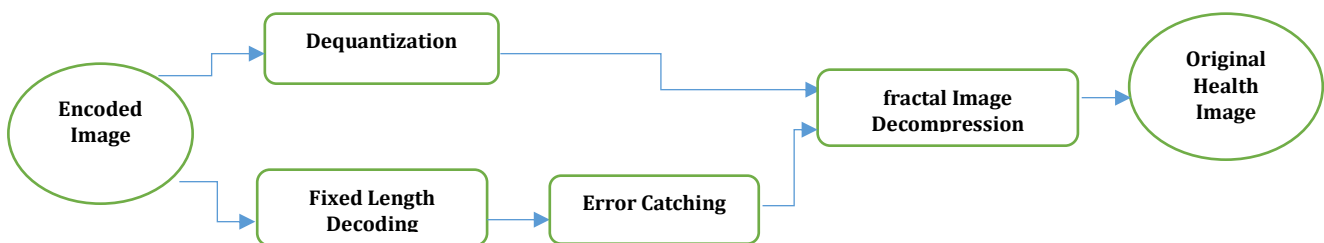


Fig. 2 -The Main Components Of SLFIC System (Decoding process)

Algorithm 1: DifferencesInputs:

H, W // Dimensions of Y Band (H: Height, W: Width)
Y[H,W], Cb[H,W], Cr[H,W]

Output:

Ydif[H,W], Cbdif[H,W], Crdif[H,W] // Color Image
Band

Main Success Scenario

```

1. For i=0 to W-1
2.   For j=0 to H-1
3.     Ydif[i, j] = Round(Y[i, j] - Ydec[i, j])
4.     Cbdif[i, j] = Round(Cb[i, j] - Cbdec[i, j])
5.     Crdif[i, j] = Round(Cr[i, j] - Crdec[i, j])
6.   Next j
7. Next i

```

Algorithm 2: Add differencesInputs:

H, W // Dimensions of Y Band (H: Height, W: Width)
Ydif[H,W], Cbdif[H,W], Crdif[H,W]
Ydec[H,W], Cbdec[H,W], Crdec[H,W]

Output:

Ydec[H,W], Cbdec[H,W], Crdec[H,W] // Color Image
Band

Main Success Scenario

```

1. For i=0 to W-1
2.   For j=0 to H-1
3.     Ydec[i, j]=Ydec[i, j]+Ydif[i, j]
4.     Cbdec[i, j]=Cbdec[i, j]+Cbdif[i, j]
5.     Crdec[i, j]=Crdec[i, j]+Crdif[i, j]
6.   Next j
7. Next i

```

Algorithm 3: Array MaxInputs:

H, W
Arr[H,W]

Output:

Maxval

Main Success Scenario

```

1. For i=0 to W-1
2.   For j=0 to H-1
3.     If Abs(Arr[i, j]) > Maxval Then
4.       Maxval = Arr[i, j]
5.     End If
6.   Next j
7. Next i

```

Algorithm 4: Wordlength, BuffersizeInputs:

Maxval

Output:

Wordlength, Buffersize

Main Success Scenario

```

1.If MaxVal <= 1 Then
2.  Wordlength = 1
3.  Else
4.    Wordlength = Round((Log(Maxval))/Log(2))+0.5)
5.End If
6.Buffersize = Round(((W * H * (Wordlength + 1))/8)+0.5)
7.End Function

```

Algorithm 1 is applied to compute the differences values, while algorithm2 used for addition operation. Furthermore, the max value and the wordlength used for encode all values have been detected by algorithm3 and algorithm4 respectively. On the other hand, the fixed length encoding and decoding operations are implemented using algorithm5 and algorithm6 respectively.

Algorithm 5: Fixed length encoding

<p><u>Inputs:</u> H, W Ydif[H,W], Cbdif[H,W], Crdif[H,W]</p> <p><u>Output:</u> Yfixedcode[H,W], Cbfixedcode[H,W], Crfixedcode[H,W]</p>	
<p><u>Main Success Scenario</u></p> <ol style="list-style-type: none"> 1. Call Array_Max(Ydif, YAbsMax) 2. Call Array_Max(Cbdif, CbAbsMax) 3. Call Array_Max(Crdif, CrAbsMax) 4. Call WordLength_BufferSize(YAbsMax, YWordLength, YBufferSize) 5. Call WordLength_BufferSize(CbAbsMax, CbWordLength, CbBufferSize) 6. Call WordLength_BufferSize(CrAbsMax, CrWordLength, CrBufferSize) <pre> // Encode Ydif(,) 7. Fco = 0 8. LeftOverBits = 8 9. For i = 0 To W - 1 10. For j = 0 To H - 1 11. If Ydif[i, j] < 0 Then ' calculate sign 12. Sn = 1 13. Else 14. Sn = 0 15. End If 16. CurrentValue = Abs(Ydif[i, j]) 17. CurrentValue <= (8 - YWordLength) // move sign to buffer 18. YFixedCode[Fco] <= 1 19. YFixedCode[Fco] = YFixedCode[Fco] Or (Sn And 1) 20. LeftOverBits = LeftOverBits - 1 21. If LeftOverBits = 0 Then 22. Fco = Fco + 1 23. LeftOverBits = 8 24. End If // move bits to buffer 25. For bco = 1 To YWordLength 26. YFixedCode[Fco] <= 1 27. YFixedCode[Fco] = YFixedCode[Fco] Or((CurrentValue And 128) >> 7) 28. CurrentValue <= 1 29. LeftOverBits = LeftOverBits - 1 30. If LeftOverBits = 0 Then 31. Fco = Fco + 1 32. LeftOverBits = 8 33. End If 34. Next bco 35. Next j 36. Next i </pre>	<pre> //Encode Cbdif(,) 37. Fco = 0 38. LeftOverBits = 8 39. For i = 0 To W - 1 40. For j = 0 To H - 1 41. If Cbdif[i, j] < 0 Then ' calculate sign 42. Sn = 1 43. Else 44. Sn = 0 45. End If 46. CurrentValue = Abs(Cbdif[i, j]) 47. CurrentValue <= (8 - CbWordLength) // move sign to buffer 48. CbFixedCode[Fco] <= 1 49. CbFixedCode[Fco] = CbFixedCode[Fco] Or (Sn And 1) 50. LeftOverBits = LeftOverBits - 1 51. If LeftOverBits = 0 Then 52. Fco = Fco + 1 53. LeftOverBits = 8 54. End If // move bits to buffer 55. For bco = 1 To CbWordLength 56. CbFixedCode[Fco] <= 1 57. CbFixedCode[Fco] = CbFixedCode[Fco] Or((CurrentValue And 128) >> 7) 58. CurrentValue <= 1 59. LeftOverBits = LeftOverBits - 1 60. If LeftOverBits = 0 Then 61. Fco = Fco + 1 62. LeftOverBits = 8 63. End If 64. Next bco 65. Next j 66. Next i // Encode Crdif(,) 67. Fco = 0 68. LeftOverBits = 8 </pre>

```
69.For i = 0 To W - 1
70. For j = 0 To H - 1
71. If Crdif[i, j] < 0 Then ' calculate sign
72.     Sn = 1
73. Else
74.     Sn = 0
75. End If
76.CurrentValue = Abs(Crdif[i, j])
77.CurrentValue <<= (8 - CrWordLength)
    " move sign to buffer
78. CrFixedCode[Fco] <<= 1
79. CrFixedCode[Fco] = CrFixedCode[Fco] Or (Sn And 1)
80. LeftOverBits = LeftOverBits - 1
81. If LeftOverBits = 0 Then
82.     Fco = Fco + 1
83.     LeftOverBits = 8
84. End If
    " move bits to buffer
85. For bco = 1 To CrWordLength
86.     CrFixedCode[Fco] <<= 1
87.CrFixedCode[Fco] = CrFixedCode[Fco] Or((CurrentValue And 128) >> 7)
88.     CurrentValue <<= 1
89.     LeftOverBits = LeftOverBits - 1
90. If LeftOverBits = 0 Then
91.     Fco = Fco + 1
92.     LeftOverBits = 8
93. End If
94. Next bco
95. Next j
96.Next i
```

Algorithm 6: fixed length decodingInputs:

H, W
Yfixedcode[W, H], Cbfixedcode[W, H], Crfixedcode[W, H]

Output:

Ydiff[W, H], Cbdiff[W,H], Crdiff[W,H]

Main Success Scenario

```

// Decode Ydiff(,)
1. Fco = 0
2. LeftOverBits = 8

3. For i = 0 To W - 1
4.   For j = 0 To H - 1

// Extract Ydiff(,)
5.   Sn = YFixedCode[Fco] And 128 //extract sign
6.   YFixedCode[Fco] <<= 1
7.   LeftOverBits = LeftOverBits - 1
8.   If LeftOverBits = 0 Then
9.     Fco = Fco + 1
10.    LeftOverBits = 8
11.   End If

12.   CurrentValue = 0
// Extract bits from buffer
13.   For bco = 1 To YWordLength
14.     CurrentValue <<= 1
15.     CurrentValue = CurrentValue Or ((YFixedCode[Fco] And
128) >> 7)
16.     YFixedCode[Fco] <<= 1
17.     LeftOverBits = LeftOverBits - 1
18.     If LeftOverBits = 0 Then
19.       Fco = Fco + 1
20.       LeftOverBits = 8
21.     End If
22.   Next bco

23.   Ydiff[i, j] = CurrentValue
24.   If Sn = 128 Then
25.     Ydiff[i, j] = Ydiff[i, j] * -1
26.   End If
27. Next j
28. Next i

//Decode Cbdiff(,)
29. Fco = 0
30. LeftOverBits = 8

31. For i = 0 To W - 1
32.   For j = 0 To H - 1

// Extract Cbdiff(,)
33.   Sn = CbFixedCode[Fco] And 128 //extract sign
34.   CbFixedCode[Fco] <<= 1
35.   LeftOverBits = LeftOverBits - 1
36.   If LeftOverBits = 0 Then
37.     Fco = Fco + 1
38.     LeftOverBits = 8
39.   End If

```

```

40.   CurrentValue = 0

// Extract bits from buffer
41.   For bco = 1 To CbWordLength
42.     CurrentValue <<= 1
43.     CurrentValue = CurrentValue Or ((CbFixedCode[Fco]
And 128) >> 7)
44.     CbFixedCode[Fco] <<= 1
45.     LeftOverBits = LeftOverBits - 1
46.     If LeftOverBits = 0 Then
47.       Fco = Fco + 1
48.       LeftOverBits = 8
49.     End If
50.   Next bco
51.   Cbdif[i, j] = CurrentValue
52.   If Sn = 128 Then
53.     Cbdif[i, j] = Cbdif[i, j] * -1
54.   End If
55. Next j
56. Next i

// Decode Crdiff(,)
57. Fco = 0
58. LeftOverBits = 8

59. For i = 0 To W - 1
60.   For j = 0 To H - 1

// Extract Crdiff(,)
61.   Sn = CrFixedCode(Fco) And 128 //extract sign
62.   CrFixedCode[Fco] <<= 1
63.   LeftOverBits = LeftOverBits - 1
64.   If LeftOverBits = 0 Then
65.     Fco = Fco + 1
66.     LeftOverBits = 8
67.   End If
68.   CurrentValue = 0

// Extract bits from buffer
69.   For bco = 1 To CrWordLength
70.     CurrentValue <<= 1
71.     CurrentValue = CurrentValue Or ((CrFixedCode[Fco]
And 128) >> 7)
72.     CrFixedCode[Fco] <<= 1
73.     LeftOverBits = LeftOverBits - 1
74.     If LeftOverBits = 0 Then
75.       Fco = Fco + 1
76.       LeftOverBits = 8
77.     End If
78.   Next bco
79.   Crdif[i, j] = CurrentValue
80.   If Sn = 128 Then
81.     Crdif[i, j] = Crdif[i, j] * -1
82.   End If
83. Next j
84. Next i

```


6. Results and Analysis

Technically, the proposed (SLFIC) system is executed and tested with eight different sizes MRI images as shown in fig.3.

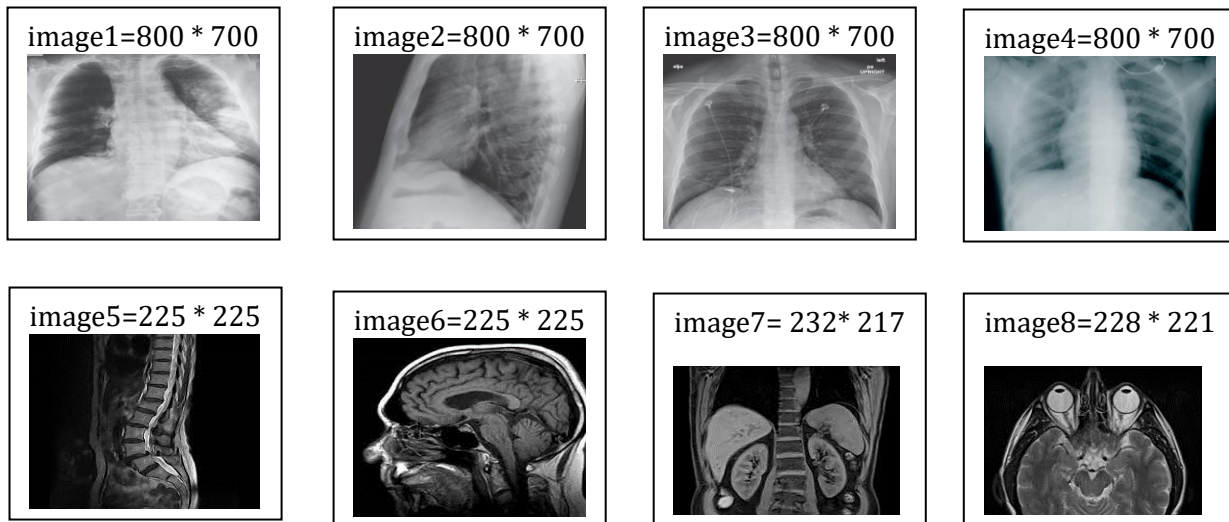


Fig. 3 - Original Image Samples With Different sizes

6.1 Evaluation metrics

The evaluation metrics have been used to evaluate our system performance on PSNR and CR. The results of the evaluation included comparisons between the proposed system and two other semi lossless systems are L2-LBG [17] and NNRBF [18].

For any image $I(m,n)$ where M, N represented the dimensions of the image, PSNR is defined as:

$$\text{PSNR} = 10 \log_{10} \left(\frac{\text{MAX}_I^2}{\text{MSE}} \right) \quad (2)$$

where MSE is computed by:

$$\text{MSE} = \frac{1}{MN} \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} [I(m, n) - \Gamma(M, N)] \quad (3)$$

where $\Gamma(M, N)$ represented the reconstructed image.

6.2 Analysis and comparisons

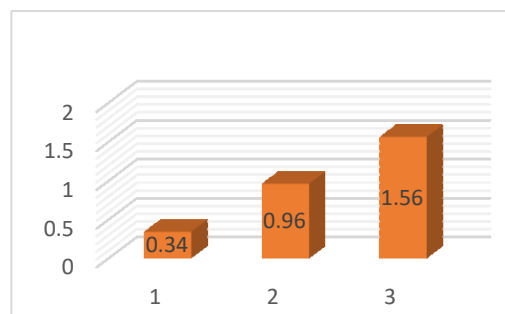
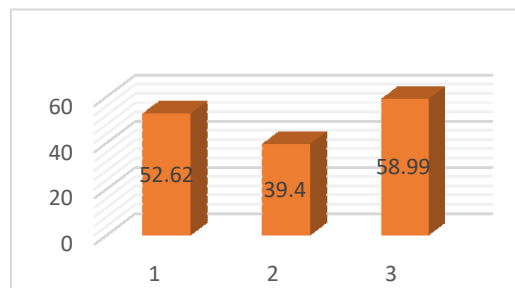
According to the test results illustrated in table1 and table2 the proposed technique (SLFIC) has a high performance when compared with the two other models NNRBF and L2-LBG. Table1 shows CR values for all models. Potentially, the proposed model (SLFIC) has outperformed the two other models where the tested samples recorded values ranging from 1.19 to 1.49 while other models have reached (0.14 - 0.58) and (0.79 - 1.07) for L2-LBG and NNRBF respectively. Moreover, table2 has gave a clear demonstration of the efficiency of the proposed model through the recorded results of PSNR metric. The outcome of the values was (58.22 - 59.78), (24.22 - 55.34) and (49.32 - 55.82) for SLFIC, NNRBF and L2-LBG respectively. fig 4 and 5 show a representation of the variance of these results .

Table 1 - CR for all models.

Samples	<i>L2-LBG</i>	<i>NNRBF</i>	<i>SLFIC</i>
image1	0.22	1.05	1.49
image2	0.21	0.93	1.41
image3	0.14	0.88	1.49
image4	0.17	0.79	1.19
image5	0.58	0.83	1.79
image6	0.52	1.05	1.71
image7	0.44	1.05	1.71
image8	0.42	1.07	1.71

Table 2 - PSNR for all models.

Samples	<i>L2-LBG</i>	<i>NNRBF</i>	<i>SLFIC</i>
image1	55.12	46.45	58.22
image2	50	30.66	58.53
image3	54.90	24.22	58.45
image4	49.32	29.98	58.35
image5	53.50	24.94	59.45
image6	51.50	55.34	59.62
image7	50.80	51.44	59.52
image8	55.82	52.18	59.78

**Fig. 4 - Compression Ratio For All Models:1-L2-LBG 2-NNRBF 3-SLFIC****Fig. 5 - PSNR For All Models:1-L2-LBG 2-NNRBF 3-SLFIC**

7. Conclusion

In conclusion, this paper has presented a new semi-lossless fractal medical image compression based on error catching concept. The main technique is based on calculating the error values of the retrieved image after decompressing the data by comparing it with the original data. The proposed technique has outperformed (NNRBF) and (L2-LBG) when comparing them in terms of PSNR and CR. Empirical results for SLFIC have been demonstrated high efficiency and accuracy with all sizes of reconstructed images.

8. References

- [1] S. S. Parikh, D. Ruiz, H. Kalva, G. Fernández-Escribano and V. Adzic, "High Bit-Depth Medical Image Compression With HEVC," in *IEEE Journal of Biomedical and Health Informatics*, vol. 22, no. 2, pp. 552-560, March 2018.
- [2] Zhongqiang Li, Alexandra Ramos, Zheng Li, Michelle L. Osborn, Xin Li, Yanping Li, Shaomian Yao, Jian Xu, An optimized JPEG-Xt-based algorithm for the lossy and lossless compression of 16-bit depth medical image, *Biomedical Signal Processing and Control*, Volume 64, 2021.
- [3] Lucas LFR, Rodrigues NMM, da Silva Cruz LA, de Faria SMM. Lossless Compression of Medical Images Using 3-D Predictors. *IEEE Trans Med Imaging*. 2017.
- [4] M. Hernández-Cabronero, V. Sanchez, I. Blanes, F. Aulí-Llinàs, M. W. Marcellin and J. Serra-Sagrístà, "Mosaic-Based Color-Transform Optimization for Lossy and Lossy-to-Lossless Compression of Pathology Whole-Slide Images," in *IEEE Transactions on Medical Imaging*, vol. 38, no. 1, pp. 21-32, Jan. 2019.
- [5] Hasanujjaman, A. Banerjee, U. Biswas and M. K. Naskar, "Fractal Image Compression of an Atomic Image using Quadtree Decomposition," 2019 *Devices for Integrated Circuit (DevIC)*, 2019.
- [6] R. Suresh Kumar, P. Manimegalai, Near lossless image compression using parallel fractal texture identification, *Biomedical Signal Processing and Control*, Volume 58, 2020.
- [7] Khaitan, Sspriya & Agarwal, Rashi. (2019). Multi-Fractal Image Compression. 340-345. 10.1109/COMITCon.2019.8862190.
- [8] Runwen Hu, Shijun Xiang, Lossless robust image watermarking by using polar harmonic transform, *Signal Processing*, Volume 179, 2021.
- [9] Chaurasia, Vijayshri & Gumasta, Rakesh & Kurmi, Yashwant. (2017). Fractal image compression with optimized domain pool size.
- [10] Raghavendra, C., Sivasubramanian, S. & Kumaravel, A. Improved image compression using effective lossless compression technique. *Cluster Comput* 22, 3911-3916 (2019).
- [11] W. Li, Q. Pan, J. Lu and S. Li, "Research on Image Fractal Compression Coding Algorithm Based on Gene Expression Programming," 2018 17th International Symposium on Distributed Computing and Applications for Business Engineering and Science (DCABES), 2018.
- [12] Sujitha, B, Parvathy, VS, Lydia, EL, Rani, P, Polkowski, Z, Shankar, K. Optimal deep learning based image compression technique for data transmission on industrial Internet of things applications. *Trans Emerging Tel Tech*. 2021.
- [13] Ilango, S. & Seenivasagam, V. & Ramamurthy, Madhumitha. (2019). Hybrid two-dimensional dual tree—biorthogonal wavelet transform and discrete wavelet transform with fuzzy inference filter for robust remote sensing image compression. *Cluster Computing*.
- [14] Fan, Chunxiao & Hu, Zhou & Jia, Lu & Min, Hai. (2021). A novel lossless compression encoding framework for SAR remote sensing images. *Signal, Image and Video Processing*.
- [15] Dhiah Al-Shammary, Ibrahim Khalil, Zahir Tari, Albert Y. Zomaya, Fractal self-similarity measurements based clustering technique for SOAP Web messages, *Journal of Parallel and Distributed Computing*, Volume 73, Issue 5, 2013.
- [16] D. Al-Shammary and I. Khalil, "Dynamic Fractal Clustering Technique for SOAP Web Messages," 2011 IEEE International Conference on Services Computing, 2011.
- [17] Geetha, K, Anitha, V, Elhoseny, M, Kathiresan, S, Shamsolmoali, P, Selim, MM. An evolutionary lion optimization algorithm-based image compression technique for biomedical applications. *Expert Systems*. 2020.

-
- [18] B. Perumal & Rajasekaran, M.. (2015). Efficient image compression techniques for compressing multimodal medical images using neural network radial basis function approach. *International Journal of Imaging Systems and Technology*.
- [19] W. Alawsy, Z. Oleiwi, A. Alwan, M. Fadhil, H. Hadi, and N. Hadi, "Performance Analysis of Noise Removal Techniques For Digital Images", *JQCM*, vol. 12, no. 1, pp. Comp Page 15 -, Feb. 2020.
- [20] A. Abdulelah, S. Abed Hamed, M. RASHEED, S. SHIHAB, T. RASHID, and M. Kamil Alkhazraji, "The Application of Color Image Compression Based on Discrete Wavelet Transform", *JQCM*, vol. 13, no. 1, pp. Comp Page 18 -, Feb. 2021.
- [21] H. Z. Neima, "Brain MRI Enhancement using Brightness Preserving Dynamic Fuzzy Histogram Equalization", *JQCM*, vol. 6, no. 1, pp. 38-51, Aug. 2017.
- [22] A. Ali, M. RASHEED, S. SHIHAB, T. RASHID, and S. Abed Hamed, "A Modified Heat Diffusion Based Method for Enhancing Physical Images", *JQCM*, vol. 13, no. 1, pp. Comp Page 77 -, Mar. 2021.
- [23] T. A. Al-Assadi and Z. Hussain Khalil, "Image Compression By Using Enhanced Fractal Methods", *JQCM*, vol. 3, no. 1, pp. 231-241, Sep. 2017.
- [24] A. Hanon Hassin AlAsadi, "Contourlet Transform based Method for Medical Image Denoising", *JQCM*, vol. 7, no. 1, pp. 146-159, Aug. 2017.
- [25] R. M. Ghadban, "Medical Image Enhancement based on Adaptive Histogram Equalization and Contrast Stretching", *JQCM*, vol. 6, no. 1, pp. 28-37, Aug. 2017.
- [26] H. Z. Neima, "Brain MRI Enhancement using Brightness Preserving Dynamic Fuzzy Histogram Equalization", *JQCM*, vol. 6, no. 1, pp. 38-51, Aug. 2017.