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Application of Krill Herd Algorithm to Improved Quasi Lossless Fractal Image Compression

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Abstract

This paper wields Krill Herd (KH) algorithm to Improved Quasi Lossless Fractal Image Compression to produce better image quality. As a sort of the swarm intelligence-based algorithm it absolutely stimulates herding attitude of the krill swarms to search the nature food. KH algorithm speeds up the execution of improved quasi lossless fractal image compression technique's execution then produces better optimization result compared to other algorithms. It focuses on minimizing the encoding time and increasing the compression ratio without any depletion in the reconstructed image quality. Additionally, experimental results of KH algorithm for various images are compared with other optimization algorithms. Their quality measures are analyzed based on encoding time, compression ratio and PSNR value.

Keywords: *Compression Ratio, PSNR, Improved Quasi lossless Fractal Image Compression, Krill Herd algorithm.*

1. Introduction

There is a need for image compression technique, since storage and transmission of audio or video files takes larger time. Image compression techniques of various kinds are developed nowadays. One among those is fractal image compression method. As a lossy compression method, it is accustomed to compress images that contain affine redundancy. In the FIC technique, the self-transformability feature is presumed and utilized. Compression of fractals can be used to generate very small files that decompose very quickly, but it is computation intensive and time consuming as it involves pixel-to-pixel comparison between the image blocks [1, 2]. So, a simple FIC technique namely improved quasi lossless fractal image compression is used in order to diminish computations, as well as decreases the encoding time. But it faces the challenges of maintaining parameters such as reconstructed image quality, PSNR (Peak Signal to Noise Ratio). Increased value of PSNR improves image quality. Meta heuristic optimization algorithm is used to increase the performance of improved quasi lossless fractal image compression. Usually optimization algorithms play a major role in FIC techniques. It enhances the performance of FIC technique used and produces the better result. Recently, many researchers and engineers are doing a lot of researches on fractal image compression. Several types of optimization algorithms such as Genetic Algorithm, Particle Swarm Optimization algorithm, Flower Pollination Algorithm, etc. are developed and used to boost the FIC. In this paper, KH optimization algorithm is approached to improved quasi lossless fractal image compression. KH algorithm is one of the swarm intelligent based optimization algorithm depends on krill individuals herding attitude. It produces better optimized result for different images. In this work, KH algorithm is also compared to PSO and FPA. This paper focuses on the performance of KH for different magnetic resonance images and their experimental results are compared to others to manifest KH algorithm works better.

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2. Improved Quasi Lossless Fractal Image Compression

A machine Learning process based on a self-organizing neural network is used in this method, in order to gather the domain and range blocks. Grouping of these blocks decreases the search space and increase algorithm's compression speed [3, 4]. To learn a data's probabilistic design, unsupervised learning is considered. Though there is no supervision or reward for the unit, for a new input considering former inputs, a design portraying probability diffusion is estimated. Proficient communication and data compression can be achieved with a probabilistic model. To portray multidimensional data in considerable underneath dimensional spaces Self-Organizing Feature Maps or SOMs is utilized. Vector quantization is data compression technique, which decreases vectors dimensionality. Furthermore, to cumulate data's the Kohonen method develops a system which in turn in the training set, it maintains physiographical interrelations. Besides clustering, generally regions with same features are identified close to one another. Main attribute of SOM is directed towards the division of training data minus some exterior administration and training. However, it requires no target vector. Self-organizing map learning is to equate various SOM interlace areas to lattice to retaliate comparable feed in designs.

SOM Algorithm

1. Initialize steps: weight vectors of map junctions
2. Grasp feed in vector
3. Track every junction not beyond the map
4. Utilize the principles of Euclidean distance to identify comparability allying feed in vector as well as weight vector of map junctions.
5. Crossover node or junction issues trivial range (this junction refer to Best Matching Unit or BMU)
6. Drag junctions nearer to input vector and in turn upgrade junctions towards BMU vicinity $Wv(t + 1) = Wv(t) + \Theta(t)\alpha(t)(D(t) - Wv(t))$

As to comprehend a SOM, there are two choices. Entire vicinity weights are progressed towards identical path in the training phase; equivalent units incline to create adjoining neurons. Thus, SOM produces a semantic map whereas identical samples are mapped side by side and disparate aside. Another way to comprehend neuronal weights intends to assume just as feed in space pointers. Together distinct estimation of diffusion concerning training samples are formed. Numerous neurons indicates regions accompanied by peak training sample concentration where as little indicates sparse samples. Matlab's neural network toolbox is used to easily build a SOM (neural network).

2.1 Improved Quasi Lossless Fractal Image Compression process

Compression process of the improved quasi lossless fractal image compression is listed below. Initial points are identical to former. Along with the former method, to boost the process of compression a supervised learning algorithm is utilized.

Compression

1. Study feed in image I.
2. Disintegrate image I as several different sized non-overlapping blocks utilizing quad tree decomposition method.
3. Segregate entire attribute high blocks of $d_{min} \times d_{min}$ size from the disintegrated image using the domain-range block separation algorithm, it denotes domain blocks then the left out part are presumed as range blocks.

4. Arrange two sets of n Groups out of Domain Blocks 6along with Range blocks, depends on blocks attribute utilizing a supervised classification technique.
5. Identify the group label as well as best identical domain block out of correlated domain block transformation for range block.

De-compression

Below indicates process of decompression accomplished utilizing fractal IFS code is given as.

1. Pile the stored coefficients as well as seed blocks.
2. Produce memory buffers aimed at range screens.
3. Regenerate attribute high parts held by range screen straight out of seed blocks (lossless area).
4. Usage of seed blocks employs transformation as well as left out part of range screen is regenerated (lossy area).
5. Regenerate hard blocks and even blocks from IFS code cause they are saved without any compression.
6. IFS code is used to redevelop entire remaining blocks out of stored seed blocks.

3. Particle Swarm Optimization Algorithm

Particle swarm optimization (PSO) is a type of optimization approach proffered by Kennedy and Eberhart in 1995. PSO developed by Kennedy and Eberhart depends on the concept of population [5, 6]. It is easy at the same time eloquent utilized to resolve different types of optimization problems. PSO operation consists of five parts which are initialization, velocity upgrading, position upgrading, memory upgrading and dissolution examining. Initial population and swarm range are the two key factors in this algorithm. Initial population refers to some initialized particles whereas selected particles numbers are nothing but swarm range by primary pressured solutions. Every particle is loaded based on personal best and global best at that each and every particles alters its positions and velocities. To acquire a solution that is to attain best solution which is pBest or gBest, a fitness function is used.

$$V_i^{t+1} = V_i^t + K_1 * rand() * (P_i - X_i^t) + K_2 * rand() \, x * (G^t - X_i t) \quad (1)$$

$$X_i^{t+1} = X_i^t + V_1^{t+1} \quad (2)$$

In t^{th}iteration, $V_i^t$is the velocity and X_i^trefers to i^{th} particle position. $P_i$denotesi^{th} particle pBest. At t^{th}iteration indicates gBest. K_1 as well as K_2specifies speed elements with value 2. With interval [0,1] rand () refers random function. We can define the fitness function as equation (3) gives the fitness function. Threshold value is determined based on the maximum fitness value given by function. The fitness function is,

$$f(t) = F0 + F1 \quad (3)$$

PSO Algorithm steps:

1. Load each and every particle.
2. Enumerate the fitness value and personal best (pBest) for each particle.
3. Compute Global Best values for every particle.

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4. Upgrade new positions and velocities.
5. Redo the steps 2 to 4 till stopping indicator achieved.

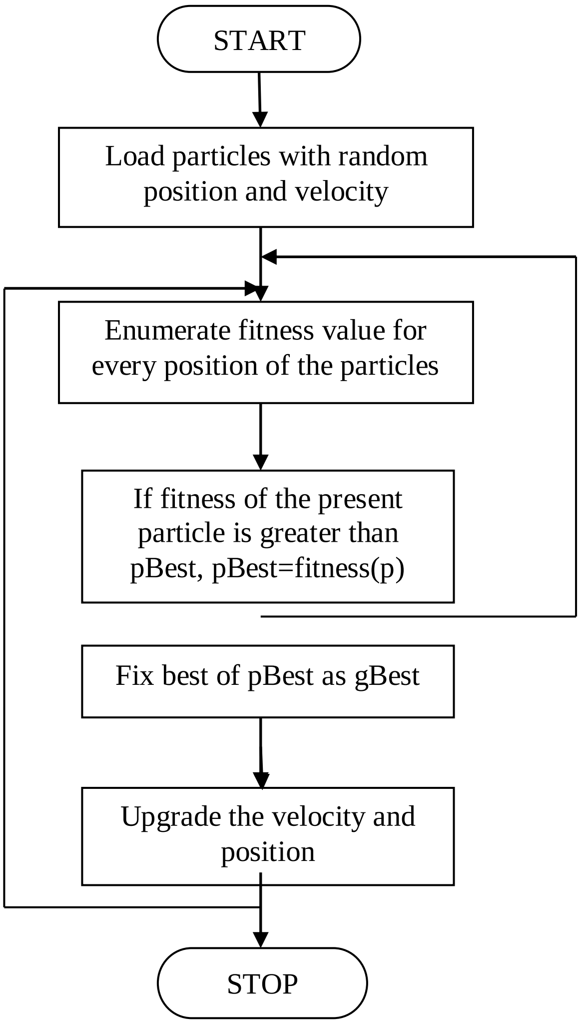

Figure 1. Flowchart of PSO Algorithm

4. Flower Pollination Algorithm

Pollination happens as soon as pollens in the flower's male parts known as anther shifted to the female part known as stigma. Fusion of gametes causes reproduction within plants. Distinct portions of flower generate male gametes and female gametes which in turn creates pollens and ovules respectively. Important factor is that the pollen should be shifted to the stigma for fusion. In flower, pollination is the action of movement and discharge of pollens between anther and stigma [7, 8 and 9].Usually agent assists the pollination's action. Cross pollination and Self-pollination are the two main types of pollination.

Relocation of pollens from distinct plants is cross-pollination. Birds and insects which flies for prolonged range is responsible for the biotic and cross pollination. Thus birds and insects acts as global pollinators. Generally, they go behind Levy flight behavior and their moves are regarded as discrete jumps that accept the Levy distribution. Self-pollination helps to reach fertilization. It takes place with the help of pollen inside the very same flower. Pollinators are not essential for self-pollination.

To solve multi-objective optimization FPA has been used. The four rules below help to achieve easy accessibility.

Rule 1: Global pollination operation contemplates biotic cross-pollination. Pollen carries pollinators and travels in the path that follows Lévy flights.
Rule 2: Local pollination makes use of self and abiotic pollination.
Rule 3: Flower constancy parallel to reproduction probability, which is correlated to the resemblance of mixed-up flower is produced by birds and insects which acts as pollinators.
Rule 4: Switch probability *p* in [0, 1] holds responsible for communication and diversion of both pollinations.

Above steps are systematized as mathematical expressions which are,

f(x) denotes minimum or maximum objective, where x = (x1, x2 ,. . . , xd)
Format 'n' number of flowers population using arbitrary results
Obtain (g*), the best solution within primary population
P in [0, 1] exhibits a switch probability
While (t < Max Generation)
For i = 1: n
If rand is less than switch probability
Sketch a (d-dimensional) step vector L from a Levy distribution
Global pollination over $X_i^{t+1} = X_i^t + \gamma L\,(g^* - X_i^t)$,
else
Outline $\in$ out of a uniform distribution in [0, 1]
Execute local pollination over
$X_i^{t+1} = X_i^t + \in (X_j^t - X_k^t)$,
end if
Estimate current resolution
If they are better, upgrade current solution in population
end for
Locate latest solution
end while
Outrun the ideal solution acquired

Theory is FPA operates at local and global stages. However, truth is that local pollination works better compared to global pollination in FPA. To overcome this problem, a proximity probability p from Rule 4 is utilized powerfully to shift between rigorous local pollination to recurrent global pollination.

5. Krill Herd Algorithm

It is one of the nature-inspired meta heuristic optimization algorithm which follows of the simulation of the herd attitude of krill throngs' concept. It is a new universal speculative optimization outlook for the global optimization problem. In KH, the location of food and each krill throngs or individuals position and its minimum distance are regarded as objective function. Optimization procedure of KH is based on three steps [10-14], which are:

i. Movement induced by other krill individuals (N_i);
ii. Foraging activity (F_i)
iii. Random diffusion (D_i).

In this method, the lagrangian model utilized within predefined search space might be expressed as,

$\frac{dXi}{dt} = N_i + F_i + D_i$ (1)

5.1 Movement induced by other krill individuals (N_i)

The movement direction $\propto_i$ for the first motion, can approximately be splitted into the three subsequent factors: the target effect, the local effect and the repulsive effect. In regards to krill individual, all these factors are given as:

$N_i^{new} = N^{max} \propto_i + \omega_n N_i^{old}$ (2)

Where

$\propto_i = \propto_i^{local} + \propto_i^{target}$ (3)

and N^{max}refers to maximum actuated speed, inertia weight in [0, 1] is denoted by ω_n, $N_i^{old} i$ points out the actuated final motion, $\propto_i^{local}$indicates the local effect issued by neighbours and $\propto_i^{target}$implies the effect of target direction which is laid out by best krill individual.
In addition, $\propto_i^{local}$can be deliberated as follows:

$\propto_i^{local} = \sum_{j=1}^{NN} \widehat{K}_{ij} \widehat{X}_{ij}$ (4)

$\ddot{X}_{ij} = \frac{X_j - X_i}{\|X_j - X_i\| + \varepsilon}$ (5)

$\ddot{K}_{ij} = \frac{K_i - K_j}{K^{worst} - K^{best}}$ (6)

where K^{worst} and K^{best} accordingly are krill's best and worst fitness K_i stands i^{th} krill fitness$K_j$constitutesj^{th} krill fitness,$K_j$exemplifiesj^{th}(j = 1, 2, . . ., NN) neighbor fitness; the allied positions are denoted as *X*, and the number of the neighbors is symbolized as NN.

Furthermore, $\propto_i^{target}$can be written as:

$\propto_i^{target} = C^{best} \widehat{K}_{i,best} \widehat{X}_{i,best}$ (7)

The irresistible coefficient of the krill individual along with the best fitness to the i^{th}krill individual best fitness is represented as C^{best}.

5.2 Foraging activity (F_i)

In KH, the foraging activity is comprised of two parameters: location of food and its past occurrence regarding food's location.

Considering the i^{th} krill individual, it is given as:

$F_i = V_f \beta_i + \omega_f F_i^{old}$ (8)

where,

$\beta_i = \beta_i^{food} + \beta_i^{best}$ (9)

and the foraging speed is denoted as V_f, the inertia weight within interval [0, 1] is indicated as ω_f, the final foraging movement is referred as F_i^{old},β_i^{food}points out the captivate foodi^{th} krill best fitness outcome is established in the population till date is implied as β_i^{best}.

5.3 Physical diffusion (D_i)

It is substantially arbitrary procedure for the krill individuals and all together, it researches the search space. This process consists of two elements which are maximum speed of diffusion and a random directional vector:

$D_i = D^{max} \delta$ (10)

Where D^{max} denotes the maximum speed of diffusion, and δ denotes the random directional vector.

6. Results and Discussions

The execution of improved quasi lossless fractal image compression has been investigated using five different images and they are displayed in the figures 2.1, 2.2, 2.3, 2.4 and 2.5 respectively. The KH algorithm using herding behavior tends to resolve continuous optimization problems in a simple manner. Results of these images are analyzed by using standard compression criterion like Peak Signal Noise Ratio, Compression Ratio, Compression Time and Decompression Time. Generally, PSNR is used to compare quality of image compression. Compression performances are estimated by the compression ratio. It is proved that the reconstructed image using KH algorithm achieves good quality much close to original input image compared to PSO algorithm and FPA. PSNR value is generally measured in decibels whereas compression ratio is measured in seconds.

$$\text{PSNR} = 20\, log_{10} \frac{255}{\sqrt{MSE}}$$

Compression efficiency is measured via compression ratio.

where, $$\text{CR} = \frac{\text{Original image size}}{\text{Compressed image size}}$$

Figure 2.1 (a) Original image1 (b) Decompressed image1 using PSO (c) Decompressed image1 using FPA (d) Decompressed image1 using KH

Figure 2.2 (a) Original image2 (b) Decompressed image2 using PSO (c) Decompressed image2 using FPA (d) Decompressed image2 using KH

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Figure 2.3 (a) Original image3 (b) Decompressed image3 using PSO (c) Decompressed image3using FPA (d) Decompressed image3 using KH

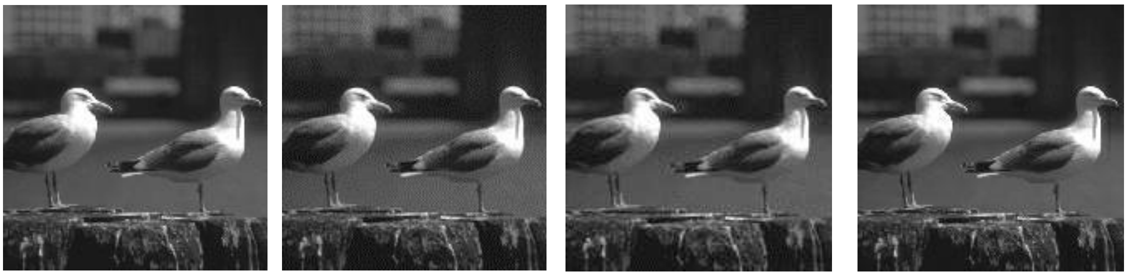

Figure 2.4 (a) Original image4 (b) Decompressed image4 using PSO (c) Decompressed image4 using FPA (d) Decompressed image4 using KH

Figure 2.5 (a) Original Image5 (b) Decompressed image5 using PSO (c) Decompressed image5 using FPA (d) Decompressed image5 using KH

Table 1. Comparison results of improved quasi lossless fractal image compression using PSO, FPA and KH for five different images

Images	Algorithm	Population size	Iteration	PSNR	Compression time (s)	Decompressi on time (s)	Compression ratio
Image1	PSO	20	100	27.63146788	52.84543561	34.52146546	8.54322276
	FPA	20	100	28.84357764	47.54156748	29.81139483	10.26787870
	KH	20	100	29.26534654	46.83226097	29.26379854	10.63354679
Image2	PSO	20	100	25.67320144	48.41032165	33.81455738	8.93023472
	FPA	20	100	27.54046781	42.32256673	28.80183562	10.86759870
	KH	20	100	27.93654768	41.96874452	28.24675699	10.96000423
Image3	PSO	20	100	30.43678347	56.92132465	39.24678984	8.58771008
	FPA	20	100	33.86320098	51.20980967	31.98967453	10.34782341
	KH	20	100	34.21777694	50.87965341	31.33578611	10.75687493

Image4	PSO	20	100	29.08789934	55.24098679	34.98918306	9.56487645
	FPA	20	100	31.65193576	49.53874098	29.26745544	10.42438768
	KH	20	100	31.97228045	49.21786552	28.83213432	10.68223567
Image5	PSO	20	100	30.26193467	56.94091265	37.01678387	9.63503483
	FPA	20	100	35.04236754	52.15900576	31.94335742	10.74447231
	KH	20	100	35.31999275	51.58327894	31.56290342	10.88048765

The performance analysis of PSO, FPA and KH is presented in Table 1 for five different images. The use of KH algorithm along with improved quasi lossless fractal image compression helps to increase compression ratio, PSNR along with slender development in compression and decompression time. The combination of improved quasi lossless fractal image compression (IQLFIC) and KH algorithm provides best results contrast to other fractal image compression techniques and algorithms. For instance, on test image 1, the IQLFIC-KH technique has occasioned a higher PSNR of 29.265347dB whereas the IQLFIC-PSO and IQLFIC-FPA techniques have led to a reduced PSNR of 27.631468dB, and 28.843578dB correspondingly. This IQLFIC technique can be utilized for different MR images as well as other engineering and medical applications.

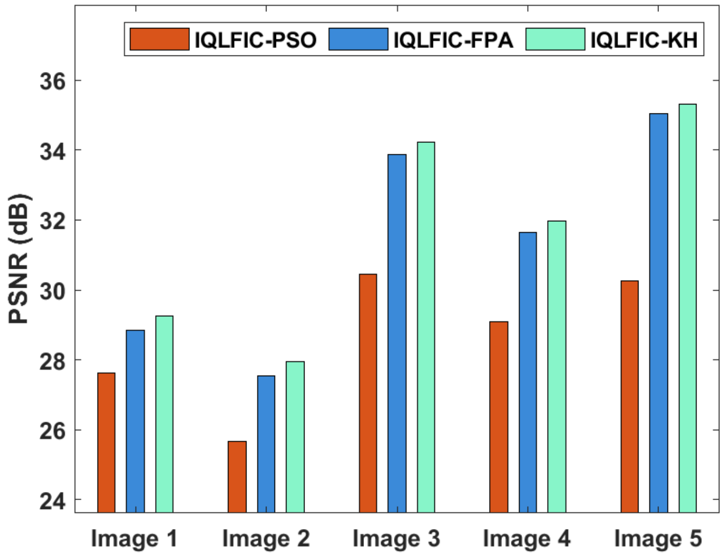

Figure 3 PSNR analysis ofIQLFIC-PSO, IQLFIC-FPA, and IQLFIC-KH techniques on standard images

Table 1 delivers a thorough comparative CT, DT, and CR analysis of the IQLFIC-PSO, IQLFIC-FPA, and IQLFIC-KH techniques on the test standard images. Figure 4 exemplifies the CT analysis of the three optimization techniques viz. IQLFIC-PSO, IQLFIC-FPA, and IQLFIC-KH techniques. The figure shows that the IQLFIC-KH technique demands a lower CT over the further compared IQLFIC-PSO and IQLFIC-FPA techniques.

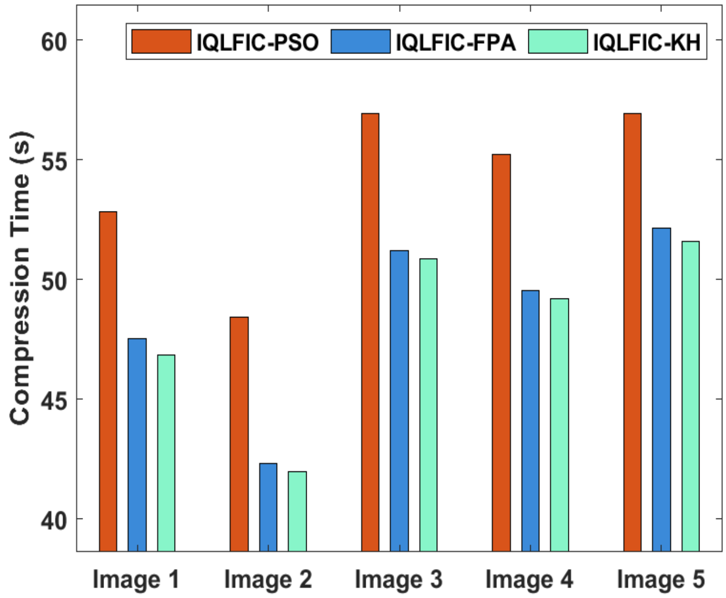

Figure 4 CT analysis of IQLFIC-PSO, IQLFIC-FPA, and IQLFIC-KH techniques on standard images

Figure 5 demonstrates the DT examination of the three optimization techniques namely IQLFIC-PSO, IQLFIC-FPA, and IQLFIC-KH techniques. The figure exhibits that the IQLFIC-KH technique imposes a lower DT over the other compared IQLFIC-PSO and IQLFIC-FPA techniques. For instance, on test image 1, the IQLFIC-KH technique has accomplished a lower DT of 29.263799s whereas the IQLFIC-PSO and IQLFIC-FPA techniques have exhibited a higher DT of 34.521465s, and 29.811395s correspondingly.

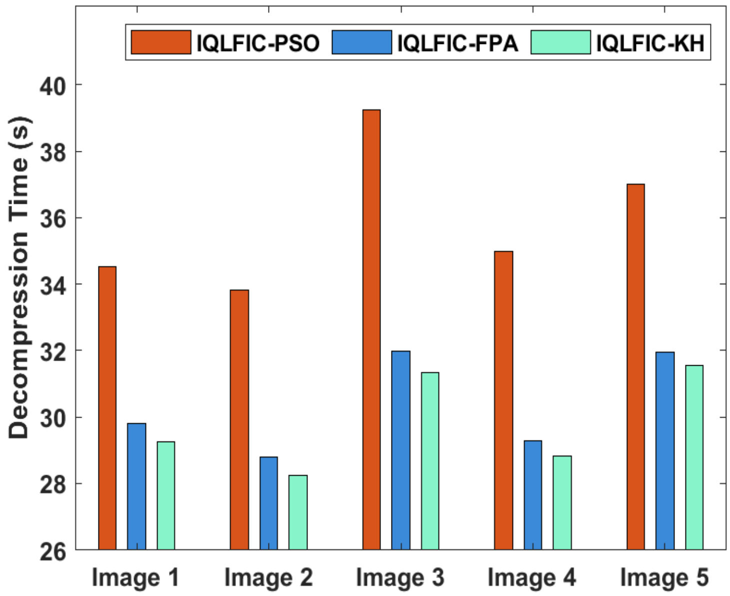

Figure 5 DT analysis of IQLFIC-PSO, IQLFIC-FPA, and IQLFIC-KH techniques on standard images

Figure 6 examines the CR analysis of the IQLFIC-PSO, IQLFIC-FPA, and IQLFIC-KH techniques on the applied five standard images. The figure revealed that the IQLFIC-KH technique has expanded effective compression performance by reaching a supreme CR. For instance, on test image 1, the IQLFIC-KH technique has got an advanced CR of 10.633547

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whereas the IQLFIC-PSO and IQLFIC-FPA techniques have confirmed an inferior CR of 8.5432228 and 10.267879 correspondingly.

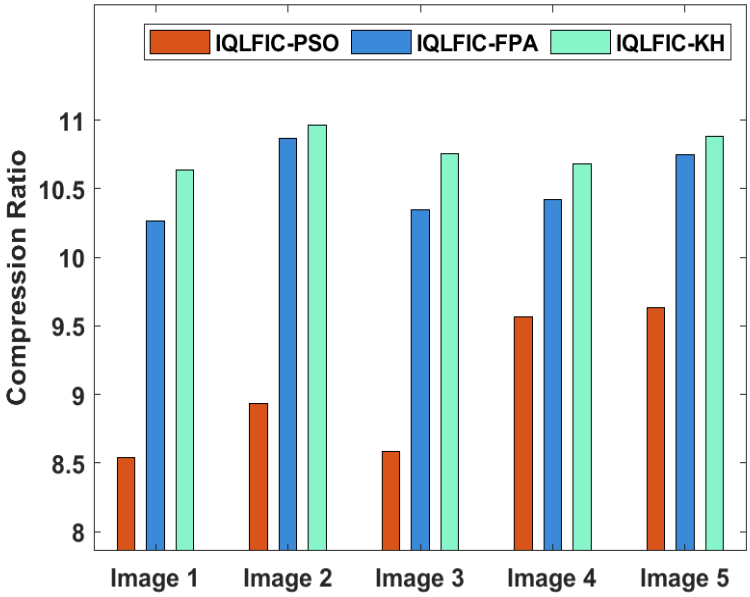

Figure 6 CR analysis of IQLFIC-PSO, IQLFIC-FPA, and IQLFIC-KH techniques on standard images

7. Conclusion

This work utilizes the concept of KH algorithm applied to improved quasi lossless FIC. Experimental results exhibit that KH offers better execution over PSO and FPA regards to improved quasi lossless FIC. Usually, the PSNR ratio for a decompressed image should be very high to have a better quality of an image and the time taken for encoding should be less. Table 1 shows that PSNR values obtained through KH are surpassing PSO as well as FPA. Also, the encoding time of KH based improved quasi lossless FIC is less than that of PSO and FPA for five input images. This image compression scheme based on KH optimization algorithm provides adequate high compression ratios without any degradation of image quality. Hence KH algorithm could be a desirable approach for improved quasi lossless fractal image compression.

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