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

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Abstract

Rage in magnetic resonance imaging technology is growing right in the direction of accessing digital images straight. Nowadays, numerous process generates images directly in digital form for instance X-ray, ECG, EEG, etc. Storage as well as transmission plays a major role in digital imaging. To overcome the difficulties owing to the increasing size of image files, there is a need for proficient image compression methods for adequate storage and transmission of medical images. To compress medical images, improved quasi lossless fractal image compression, a sort of fractal image compression technique is used. Improved quasi lossless fractal image compression improves speed of encoding by reducing the search space. This paper utilizes the Krill Herd optimization algorithm which is applied to improved quasi lossless fractal image compression to further speed up the encoder and to preserve the medical image quality. This work represents the theoretical and practical implementation of the krill herd algorithm. It is also compared to other optimization algorithms for various medical images have also been reported here.

Keywords:*Fractal Image Compression, Improved Quasi Lossless Fractal ImageCompression, Krill Herd algorithm, Optimization algorithms.*

1. Introduction

The process of medical diagnosis produces a huge amount of MR images for instance CT, MRI and ECG image. Digital X-rays are developed and used in the hospitals to monitor chest as well as breast imaging. The power of digital imaging is based on its immediate aid of transplanting and documenting images, and also exploiting and improving the probability of medical interpretation. The size of these medical images is always very large and occupies huge amount of memory space and bandwidth for transmission. For the reduction of memory space and efficient bandwidth process, there is a need for image compression technique. Compressing images is a collection of lossy and lossless compression techniques. Fractal image compression technique is promising both theoretically and practically. But it suffers from large time taken for encoding of medical images. The medical images data are valuable data without any slight loss of information. As a result of several computations and additional time needed to compress the medical images, we opt for another type of FIC technique [1-5]. In this paper, a simple FIC technique namely improved quasi lossless FIC is employed to diminish the computations, as well as to decrease the encoding time. It operates better than other FIC methods. It tries to retain the parameters like image quality, encoding time, Peak Signal to Noise Ratio (PSNR) and compression ratio (CR) at required level compared to standard FIC and quasi lossless FIC. However, usage of meta heuristic optimization algorithm highly supports fractal image compression techniques to produce optimal results. Generally, optimization algorithm plays a significant role in FIC technique. It enhances the performance of FIC

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and produces the optimal result. In this work, KH optimization algorithm is applied to improved quasi lossless fractal image compression. KH algorithm fulfilsthis requirement to a greater extent by providing the improved and optimized result for various medical images.

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. 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 [2].

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 refers 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 tool box 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 is presumed as range blocks.
4. Arrange two sets of n Groups out of Domain Blocks along 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 [6, 7]. It is easy at the same time eloquent utilized to resolve different types of optimization problems. PSO operation consists of five parts which are initialisation, 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.

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

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

In t^{th} iteration, V_i^t is the velocity and X_i^t refers 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.

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

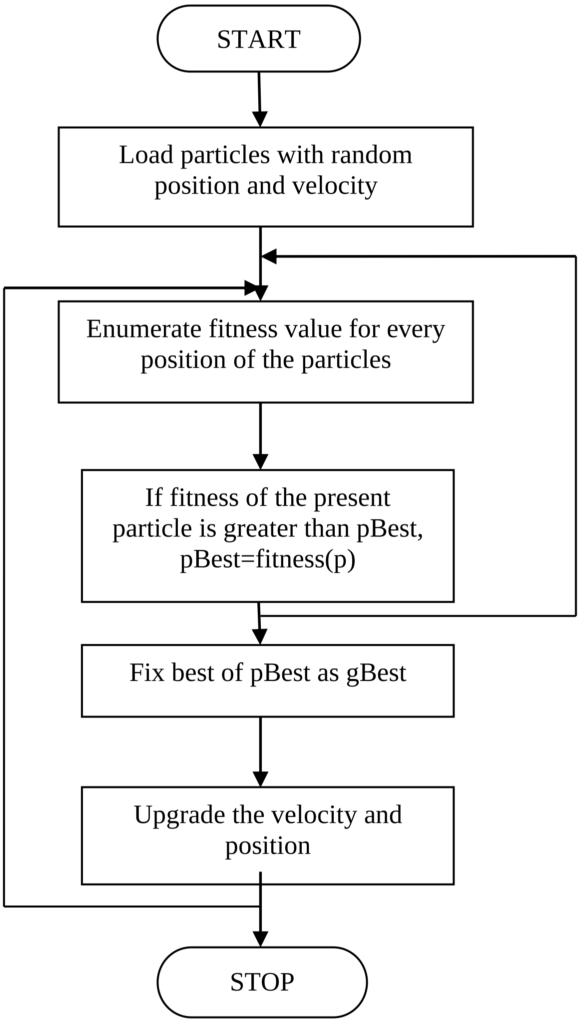

Figure 1. Flowchart of PSO Algorithm

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. 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 act as global pollinators. Generally, they go behind Levy flight behaviour 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 [8, 9].

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.

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5. Krill Herd Algorithm

Krill Herd algorithm is one of the nature-inspired algorithm which follows the concept of the simulation of the herding behaviour of krill individuals. It is a new universal speculative optimisation outlook for the global optimisation problem [10, 11]. In KH, the location of food and position of each krill individual's minimum distance is regarded as objective function. Optimization procedure of KH is based on three steps, which are:

i. Movement induced by other krill individuals (N_i);

ii. Foraging activity (F_i);

iii. Random diffusion (D_i).

In KH method, the Lagrangian model used within predefined search space can be mathematically represented as follows

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

5.1 Movement induced by other krill individuals (N_i)

The motion 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 a krill individual, all these factors are given as:

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

where

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

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:

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

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

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

where K^{worst} and K^{best} accordingly are the best and the worst fitness of the krill, K_i stands for the fitness of the *i*th krill and K_j constitutes the fitness of the *j*th krill, K_j exemplifies the fitness of jth (j = 1, 2, . . . ,NN) neighbour; the related positions are denoted as X, and the number of the neighbours is symbolized as NN .

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

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

The irresistible coefficient of the krill individual along with the best fitness to the *i*th krill individual 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 the location of food.

For the *i*th krill individual, it is given as:

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

Where,

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

and the foraging speed is denoted as V_f, the inertia weight in [0, 1] is indicated as ω_f , the final foraging motion is referred as F_i^{old},β_i^{food}points out the food attractive and the effect of the best fitness of the *i*th krill established in the population till date is implied as β_i^{best}.

5.3 Physical diffusion (D_i)

Physical diffusion is essentially a arbitrary procedure for the krill individuals and at the same time, it researches the search space. This process consists of two elements which are maximum speed of diffusion and a random directional vector:

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

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

6. Results and Discussions

Execution of Krill Herd algorithm based improved quasi lossless FIC is examined with the help of five distinct medical images. Visual representation of the improved quasi lossless fractal image compression method using PSO algorithm, FPA and KH algorithm is presented in the Fig. 2.1, 2.2, 2.3, 2.4 and 2.5 respectively for all five different medical images. It has been proved that this method achieves good quality of the reconstructed images over input images. The working of this technique is accessed with regards to performance metrics.

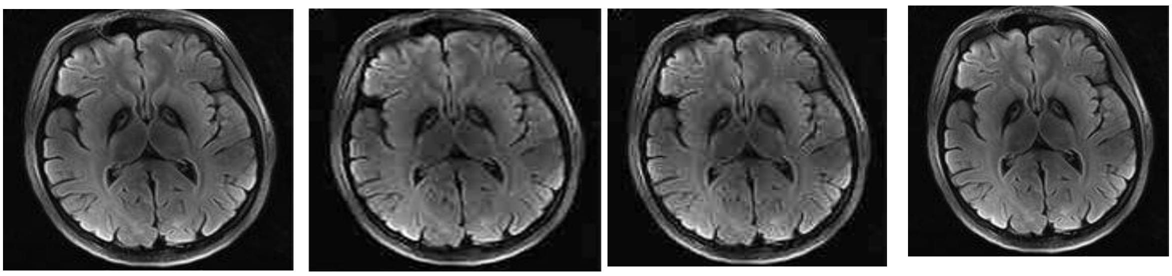

Figure 2.1 (a) Original MR image1 (b) Decompressed MR image1 using PSO (c) Decompressed MR image1 using FPA (d) Decompressed MR image1 using KH

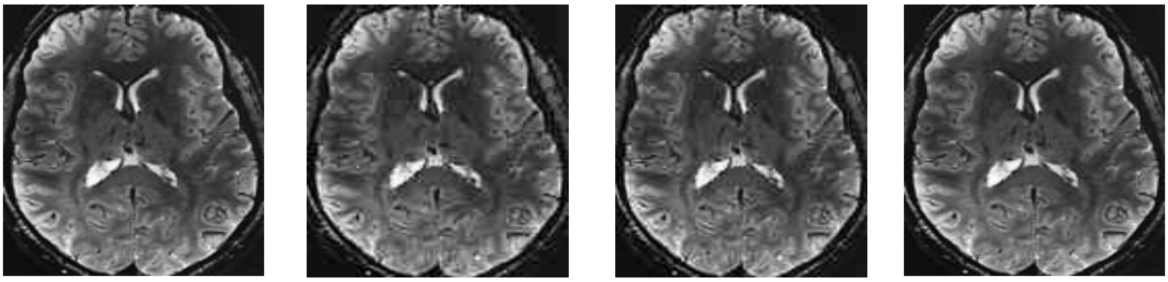

Figure 2.2 (a) Original MR image2 (b) Decompressed MR image2 using PSO (c) Decompressed MR image2 using FPA (d) Decompressed MR image2 using KH

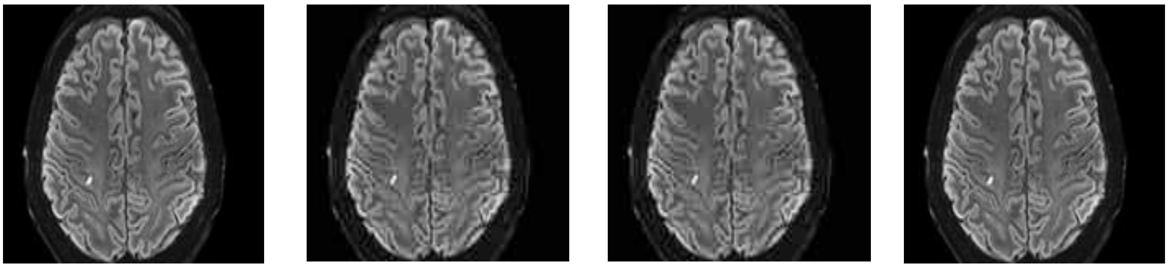

Figure 2.3 (a) Original MR image3 (b) Decompressed MR image3 using PSO (c) Decompressed MR image3 using FPA (d) Decompressed MR image3 using KH

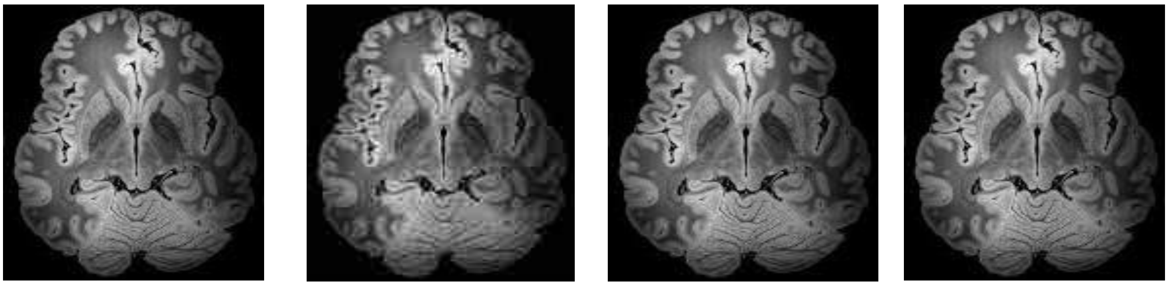

Figure 2.4 (a) Original MR image4 (b) Decompressed MR image4 using PSO (c) Decompressed MR image4 using FPA (d) Decompressed MR image4 using KH

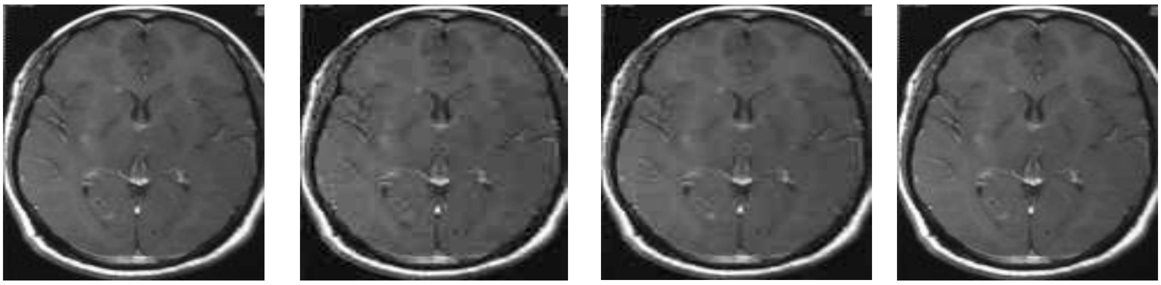

Figure 2.5 (a) Original MR image5 (b) Decompressed MR image5 using PSO (c) Decompressed MR image5 using FPA (d) Decompressed MR image5 using KH

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

MR Images	Algorithm	Population size	Iteration	PSNR	Compression time (s)	Decompression time (s)	Compression ratio
MR Image1	PSO FPA KH	20 20 20	100 100 100	24.51547653 27.56675641 27.93445876	42.70089654 38.32654768 37.85676587	31.44765767 26.84565431 26.25463454	6.83244532 7.99065456 8.11678765
MR Image2	PSO FPA KH	20 20 20	100 100 100	22.38776587 25.87008971 26.24666754	41.53588743 37.59567430 37.13465438	29.45887654 25.03444676 24.78900878	6.83356876 7.92587656 8.03467854
MR Image3	PSO FPA KH	20 20 20	100 100 100	27.34678956 28.83477812 29.31679877	43.45677689 39.53765876 39.14990567	34.48997681 29.65771342 29.22786578	7.83359980 8.79567433 8.85467321
MR Image4	PSO FPA KH	20 20 20	100 100 100	26.59900013 29.72367658 29.98567654	41.73677809 38.45698971 38.37877622	33.93989765 29.85670098 29.34673324	7.68560987 8.34667654 8.48870943
MR Image5	PSO FPA KH	20 20 20	100 100 100	28.34768889 29.98126574 30.45697877	45.44790100 41.27111435 40.83587659	35.56790887 31.54789543 30.98786488	8.02555643 8.85674536 9.12986754

During Comparative analysis, the performance of KH algorithm is compared to PSO and FPA in terms of PSNR and CR performance metrics for medical images. KH produces good decompressed quality of image much close to input image.

Table 1 illustrates that the implementation of Krill Herd algorithm to improved quasi lossless fractal image compression (IQLFIC) is equated with other optimization techniques such as PSO and FPA based on the parameters like PSNR, CT, DT and CR. Krill Herd algorithm shows higher values for different medical images using compression metrics. It provides the outcomes analysis of the QLFIC-PSO, QLFIC-FPA, and QLFIC-KH techniques in terms of PSNR on the applied 5 medical images under the fixed population size of 20 and iteration count of 100.

The table values stated that the QLFIC-PSO model has reached minimum PSNR value over the other QLFIC-FPA and QLFIC-KH techniques. Simultaneously, the QLFIC-FPA approach has resulted in a slightly increased PSNR over the QLFIC-PSO model while the QLFIC-KH approach has accomplished proficient outcomes by offering a maximum PSNR value.

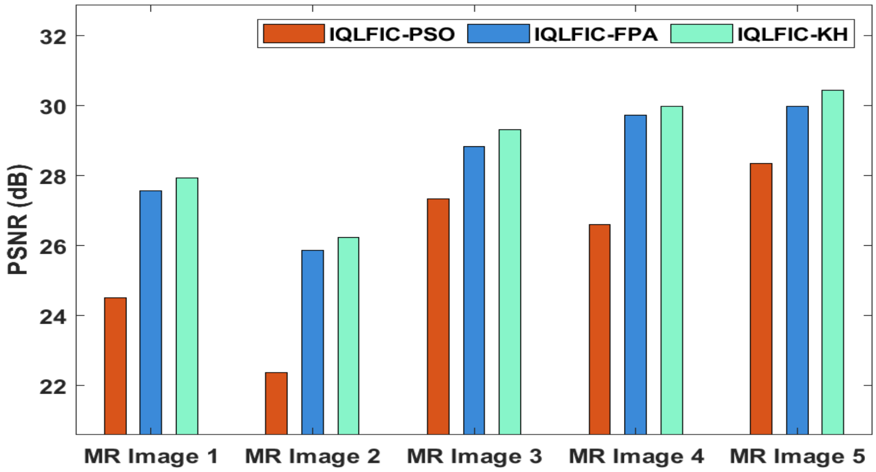

Figure 3 PSNR analysis of IQLFIC-PSO, IQLFIC-FPA, and IQLFIC-KH techniques on medical images

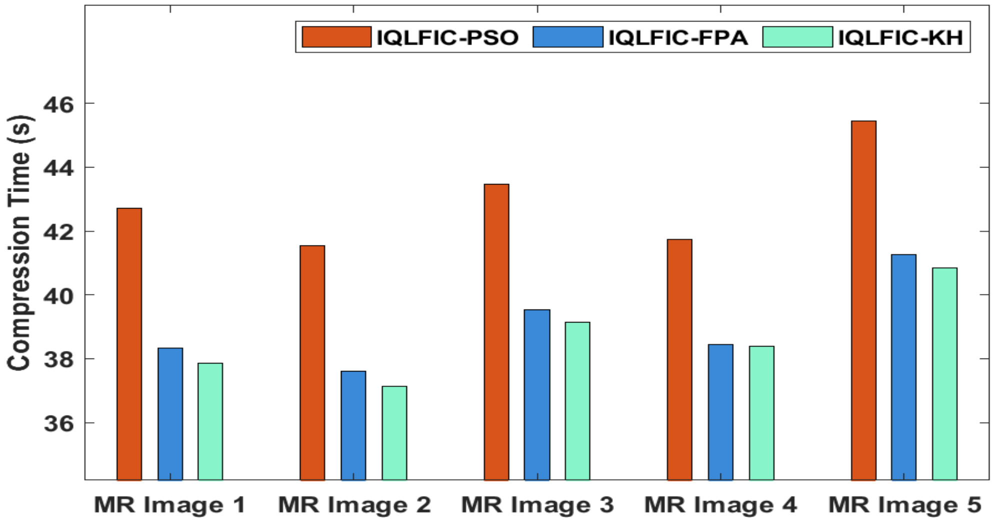

Figure 4CT analysis of IQLFIC-PSO, IQLFIC-FPA, and IQLFIC-KH techniques on medical images

For instance, on the applied MR image 1, the QLFIC-KH method has resulted in a superior PSNR of 27.54879856dB while the QLFIC-PSO and QLFIC-FPA models have led to a minimum PSNR of 23.65765498dB, and 26.98478675dB correspondingly. Likewise, on the applied MR image 2, the QLFIC-KH approach has resulted in a higher PSNR of 25.89124656dB whereas the QLFIC-PSO and QLFIC-FPA algorithms have led to a lower PSNR of 21.58783689dB, and 25.36790898dB correspondingly. In line with, on the applied MR image 3, the QLFIC-KH algorithm has resulted in a maximum PSNR of 29.25768990dB whereas the QLFIC-PSO and QLFIC-FPA methodologies have led to a lower PSNR of 26.59000234dB, and 28.74914345dB respectively. Followed by, on the applied MR image 4, the QLFIC-KH method has resulted in a higher PSNR of 29.96642431dB whereas the QLFIC-PSO and QLFIC-FPA approaches have led to a lower PSNR of 25.26787957dB, and 29.50972444dB respectively. Simultaneously, on the applied MR image 5, the QLFIC-KH algorithm has resulted in a superior PSNR of 29.98145877dB whereas the QLFIC-PSO and QLFIC-FPA methodologies have led to a lower PSNR of 27.62676560dB, and 29.57637889dB respectively.

Increased PSNR values specify that KH operates better. Therefore, it clearly justifies that application of KH algorithm to improved quasi lossless FIC optimization technique yields higher image compression results than the other algorithms.

Figure 4 demonstrates the CT analysis of the three optimization techniques such as QLFIC-PSO, QLFIC-FPA, and QLFIC-KH models. The figure showcases that the QLFIC-KH method requires a minimum CT over the other compared QLFIC-PSO and QLFIC-FPA methods. For instance, on the test MR image 1, the QLFIC-KH model has resulted in a minimum CT of 36.6815990s whereas the QLFIC-PSO and QLFIC-FPA techniques have accomplished a higher CT of 43.6076663s, and 39.2867693s correspondingly.In addition, on the test MR image 2, the QLFIC-KH method has resulted in a lower CT of 37.7589099s whereas the QLFIC-PSO and QLFIC-FPA approaches have been accomplished a superior CT of 42.3975700s, and 38.2075457s respectively.Though on the test MR image 3, the QLFIC-KH algorithm has resulted in a lesser CT of 39.2365542s while the QLFIC-PSO and QLFIC-FPA methods have accomplished a higher CT of 44.8390982s, and 39.7598989s correspondingly. Moreover, on the test MR image 4, the QLFIC-KH technique has resulted in a minimal CT of 38.3535422s whereas the QLFIC-PSO and QLFIC-FPA approaches have accomplished a higher CT of

42.5968398s, and 38.8389123s correspondingly. Furthermore, on the test MR image 5, the QLFIC-KH method has resulted in a minimum CT of 41.2867219s whereas the QLFIC-PSO and QLFIC-FPA algorithms have accomplished a higher CT of 46.5789481s, and 41.6370318s respectively.

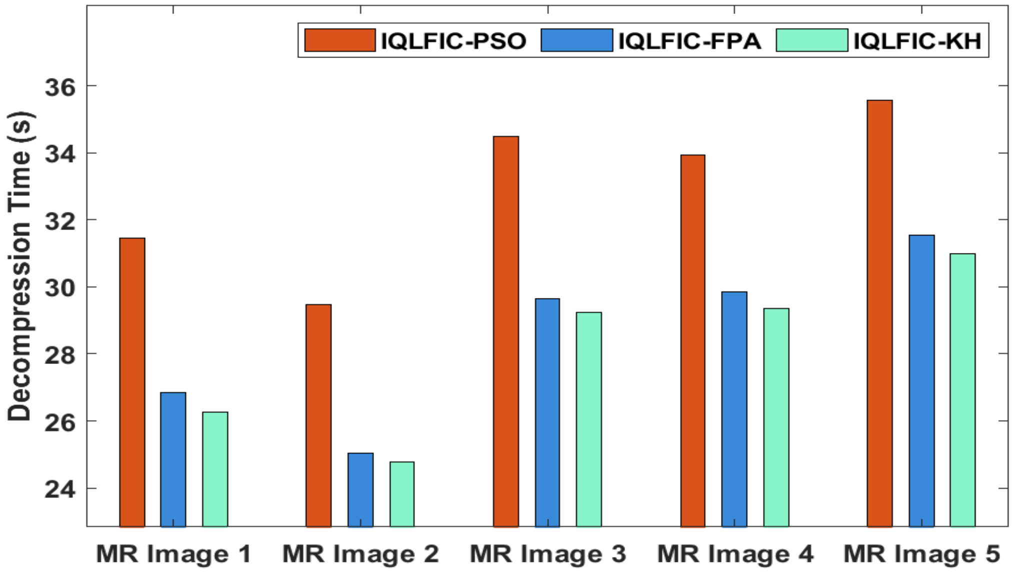

Figure 5 DT analysis of IQLFIC-PSO, IQLFIC-FPA, and IQLFIC-KH techniques on medical images

Figure 5 shows the DT results of the applied three optimization techniques namely IQLFIC-PSO, IQLFIC-FPA, and IQLFIC-KH techniques. The figure reported that the IQLFIC-KH technique incurs a lower DT over the other compared IQLFIC-PSO and IQLFIC-FPA techniques. For instance, on the test MR image 1, the IQLFIC-KH technique has resulted in a decreased DT of 26.254635s whereas the IQLFIC-PSO and IQLFIC-FPA techniques have accomplished an increased DT of 31.447658s, and 26.845654s correspondingly. In addition, on the test MR image 2, the QLFIC-KH method has resulted in a lesser DT of 24.936882s whereas the QLFIC-PSO and QLFIC-FPA methods have accomplished a higher DT of 30.546526s, and 25.565774s respectively.

In line with, on the test MR image 3, the QLFIC-KH approach has resulted in a lower DT of 29.328891s while the QLFIC-PSO and QLFIC-FPA methods have accomplished a higher DT of 35.776727s, and 29.812472s correspondingly. Along with that, on the test MR image 4, the QLFIC-KH algorithm has resulted in a lower DT of 30.566939s whereas the QLFIC-PSO and QLFIC-FPA algorithms have accomplished a higher DT of 34.854321s, and 31.095597s respectively. On the other hand, on the test MR image 5, the QLFIC-KH method has resulted in a lesser DT of 31.815460s while the QLFIC-PSO and QLFIC-FPA algorithms have accomplished a higher DT of 36.695883s, and 32.328971s correspondingly.

Figure 6 analyses the CR analysis of the QLFIC-PSO, QLFIC-FPA, and QLFIC-KH techniques on the applied five medical images. The figure exhibited that the QLFIC-KH method has gained effective compression performance by achieving a superior CR. For instance, on the applied MR image 1, the QLFIC-KH method has attained a superior CR of 7.9578424 whereas the QLFIC-PSO and QLFIC-FPA algorithms have demonstrated a lower CR of 6.7532097 and 7.7358754 correspondingly. On continuing with, on the applied MR image 2, the QLFIC-KH algorithm has reached a higher CR of 7.8735933 whereas the QLFIC-PSO and QLFIC-FPA methods have demonstrated a lower CR of 6.5579414 and 7.7258143 correspondingly. Along with that, on the applied MR image 3, the QLFIC-KH approach has reached a higher CR of 8.7808147 whereas the QLFIC-PSO and QLFIC-FPA algorithms have demonstrated a lower CR of 7.7257397 and 8.6551728 respectively.

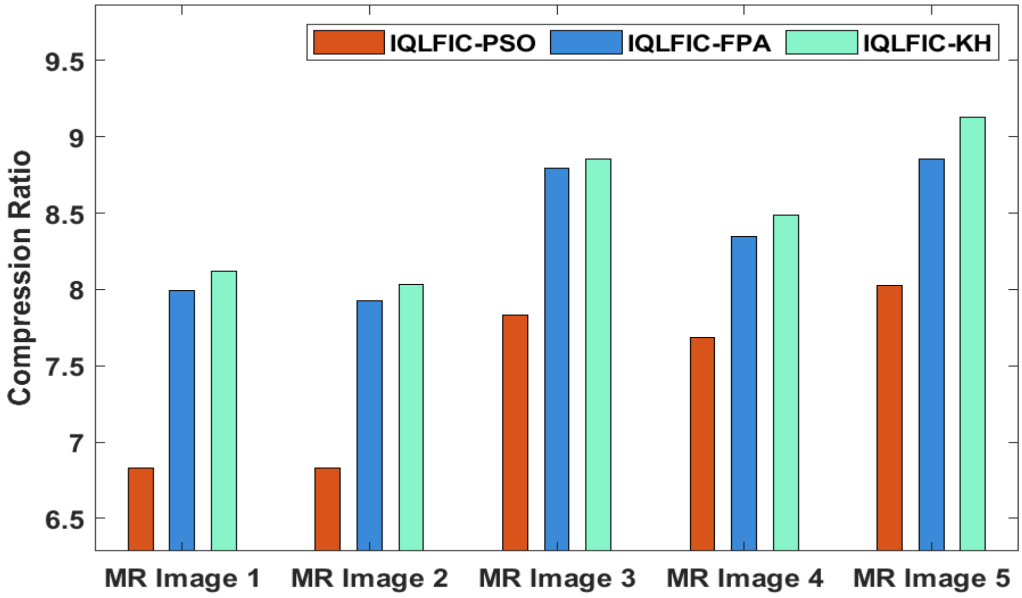

Figure 6CR analysis of IQLFIC-PSO, IQLFIC-FPA, and IQLFIC-KH techniques on medical images

Followed by, on the applied MR image 4, the QLFIC-KH manner has obtained a superior CR of 8.4281210 whereas the QLFIC-PSO and QLFIC-FPA methods have demonstrated a lower CR of .6579339 and 8.2854638 respectively. Finally, on the applied MR image 5, the QLFIC-KH method has attained a higher CR of 9.0163933 whereas the QLFIC-PSO and QLFIC-FPA approaches have exhibited a lower CR of 7.9968006 and 8.7475318 respectively. Therefore, in this work, the IQLFIC-KHA is employed to standard FIC technique as well as it is compared with IQLFIC-PSO and IQLFIC-FPA. IQLFIC-PSO is a one-way information sharing mechanism. IQLFIC-PSO technique is a global search approach, it avoids falling into local optimum solution. However, when it comes to complex problems, it fails to produce the best solution. The IQLFIC-FPA has advantages such as coherence and resilience. It does not suffer from local optima problems. It uses both global and local search techniques to find best solution. But decoded or decompressed image does have minute loss of information. KHs technique is used to get over these problems. IQLFIC-KH technique obtains good results. IQLFIC-KH performs slightly better than IQLFIC-FPA technique because it produced good results for all the images applied without any loss of information.

7. Conclusion

Algorithms discussed in this paper are swarm intelligence-based algorithms which proves to be better for all engineering problems and medical applications. In this work, Krill Herd algorithm is used to enhance improved quasi lossless fractal medical image compression and it operates better compared to PSO and FPA for medical images. This quality of image is maintained by this KH algorithm and takes less time for encoding compared to PSO and FPA. The Krill Herd algorithm is applied to medical images to retrieve the original quality without any tiny loss of information. Tabulation and execution outcomes indicate that KH algorithm works better compared to FPA and PSO.

The application of KH algorithm to improved quasi lossless fractal medical image compression has an advantage of good compression performance while retaining the quality of reconstructed images.

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