QUASI-LOSSLESS BASED FRACTAL IMAGE COMPRESSION USING KRILL HERD ALGORITHM FOR MEDICAL IMAGES

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***Abstract*— Medical imaging is one among the bustling and meteorically progressing domain in medical and research area. Evolution of medical applications leading to vast growth of medical image data needs proficient accumulation and transference. Hence, it is important to aptly compress medical data. Compression of magnetic resonance images in superior quality is obligatory. As a result, quasi lossless fractal image compression method is used for compressing medical images. To achieve better image compression and encoding time, an image compression algorithm is needed. Krill Herd algorithm is implemented for fruitful compression of various medical images in this paper. It follows the concept of simulating krill individuals herding behaviour. Krill Herd algorithm abruptly compresses different medical images and surpasses the other algorithms. In our work, Krill Herd algorithm in quasi lossless fractal medical image compression is compared with other algorithms and their performances are validated.**

***Index Terms*— Quasi Lossless Fractal Image Compression, Krill Herd algorithm, Medical images, Encoding Time, Compression ratio.**

I. Introduction

Reality is that medical images are obtained in digital format. Storage and transfer of medical images encounters significant difficulties, owing to the increasing size of these images. Image compression is one of the best methods used to overcome this issue. There is a hefty urge for medical image compression with the necessity of storage and transmission over the network or devices [1]. Image compressions comprises of Lossless compression and Lossy compression [2]. Over the years there are many types of lossless image compression and lossy image compression methods produced. In medical fields, usually any minor information loss is disagreeable since it causes major change in the outcome. Recently, area of lossy compression faces major advancements for its coherent use [3]. Fractal image compression (FIC) technique has been largely used in medical imaging because of its standard features like quick compression, greater compression ratio and self-similarity. FIC is the propitious technology. It is based on fractals and utilizes the property called self-similarity that is present in any image [4]. To encode a medical image, a mathematical process named fractal compression is used. It relies on the certainty that each and every object contains information with regards to related, repeating patterns. Encoding process consists of the large number of iterations needed to find out the fractal patterns in a medical image. Fractal image compression is categorized into quasi lossless and improved quasi lossless fractal image compression [5].

To compress medical images, quasi lossless fractal image compression method is used. It maintains the image quality and provides required high compression ratio thus utilizing the benefits of lossless and lossy techniques. The main attribute high parts of medical image are conserved as domain blocks and fractal transformations are utilized to produce the left-out part of the image [6, 7]. However, optimization algorithms play a key role in fractal image compression providing optimal solution. In this work, we use a KH algorithm, which is a simple algorithm. It is employed in quasi lossless fractal image compression scheme to acquire less encoding time and for the better compression of medical images. Also, KH algorithm is compared to PSO algorithm and FPA to monitor which works better in quasi lossless fractal image compression technique. All these above algorithms are the members of swarm intelligent type of algorithms.

The PSO has achieved the vast growth in a short period and has been used in many areas of engineering optimization. PSO simulates the societal characteristics of organisms to resolve a typically evolving system. In PSO, each element takes advantage of its individual memory and information attained by the swarm as entire to find the finest solution. PSO algorithm has the advantage such as simple concept, easy implementation, and proficient computation compared to other heuristic optimization algorithms. But it fails to make encoding process easier.

Flower pollination algorithm is swarm intelligence-based algorithm proposed in 2012 by Yang. It was prompted by natural phenomenon of pollen grains transfer from the stamens by themselves. Global and local pollination are the two ways of pollination. Generation of random position for the flowers is done originally. Global pollination, to transfer pollen to prolonged distance employs pollinators whereas the local pollination happens in finite range of discrete flower because of pollination negotiators such as wind, water, etc.

KH algorithm performs multiple target process like growing density of krill and hitting food. The range linking the location of food and the discrete krill position is regarded as target in KH algorithm. It is easy for implementation and generally it has simple concept. This algorithm constitutes three movements specifically motion induced by other krill, foraging motion and physical diffusion. Corresponding to these three movements in population the krill individuals are upgraded. Due to its benefits over other optimization methods, it has acquired remarkable contemplation from researchers and engineers.

This paper is regulated in detail as: Section 2 focuses on the concept of quasi lossless fractal image compression technique. Section 3 explains the theory of PSO whereas Section 4 and Section 5 deals with application of FPA and KH in quasi lossless FIC technique respectively. Section 6 pays attention to experimental results and discussions. In Section 7 some conclusions are drawn.

II. Quasi Lossless Fractal Image Compression

In this technique, in the block set comprises variance which in turn splits domain blocks and range blocks. The domain blocks are nothing but attribute large blocks and besides transformation coefficients, it is conserved. Quad tree decomposition technique is used to split the image 'f' into image B constituting blocks b1, b2 …bn. Range and domain block sets happens to be void sets originally. Initially, Images are segregated as vast range blocks using the quad tree decomposition process. Later, the elite transformation of every block is identified. Range block is splitted as four quadratic small-blocks then repeatedly elite transformation is explored in every small-block using the metric as long as the transformation is rejected. This process is repeated till all the blocks are covered. The ensuing tree mislays the property of symmetry, if the partition is not done in equal amount. Proportionate to s_i, minimum and maximum feasible values of o_i are confined. Selection of $\{R_i\}$∈R set and equivalent $\{D_i\}$∈D set for encoding produces better compression and image quality based on the option of R and D [8].

The time taken to identify the domains D_i is the time taken for encoding. Seed blocks are none other than attribute minted blocks. Accumulated seed blocks straightly produces attribute rich parts of the image. Fractal transformation approach helps to develop the image's left out part from the seed blocks. The depletion in time taken for compression creates a major distinction. This technique also gives better PSNR value for the decompressed image. In several images, implementation of quad tree decomposition decreases time taken for compression. Small seed blocks produce huge areas, as attribute minted areas are small and analogous areas are big which in turn reduces time taken for compression.

Behind quad tree decomposition, set of all blocks are denoted as B, set of range blocks are implied as R and set of domain blocks are noted as D and it needs to be segregated from set B, whereas B = $\{b_1, b_2, b_3, \ldots, b_n\}$, let R = { } and D = { }

For each and every block in B
Execute
{
If ($s_{b_i} > d_{min}$)
{
R ← R ∪ b_i
}
Else if ($\sigma^2_{b_i} > \sigma^2_{b_{max}} \times \tau$ and $\sigma^2_{b_i} >= \sigma^2_{b_{max}}$)
{
D ← D ∪ bi
}
Else
{
R ← R ∪ b_i
}
}

Where s_{b_i} points out the block size, d_{min} implies the minimum size of the domain block, $\sigma^2_{b_i}$ denotes the block b_i variance in set B, $\sigma^2_{b_{max}}$ stands for the maximum variance of $d_{min} \times d_{min}$ image blocks. τ indicates threshold value, which is usually among 0 and 1 also it determines domain pool proportions in addition with the characteristics of the blocks in the domain pool. As long as τ is 0, domain blocks are chosen based on the blocks of size $d_{min} \times d_{min}$. But if τ is 1, domain blocks are chosen according to the blocks of size $d_{min} \times d_{min}$ with greatest variance. Thus, the threshold value 'τ' determines the compression quality and compression time. Huge domain blocks are regenerated from the small seed blocks which gives a greater compression ratio. For instance, 32 × 32 or 16 × 16 blocks are regenerated from 2 × 2 seed block. Below algorithm directed towards procurement of greater compression ratio.

Steps for Quasi-lossless fractal image compression algorithm are as follows:

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 parts are presumed as range blocks.
4. Identify the best identical domain block, appropriate to for each range block and also note the transformation coefficients.
5. Encode domain blocks with any kind of lossless compression method then reserve as basis in addition to transformation coefficients.

III. Particle Swarm Optimization

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 [9]. 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 particles are loaded based on personal best and global best at that, each and every particles alters its positions and velocities [9]. 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^t refers to i^{th} particle position. P_i denotes i^{th} particle pBest and t^{th} iteration indicates pBest. K_1 as well K_2 specifies 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,

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

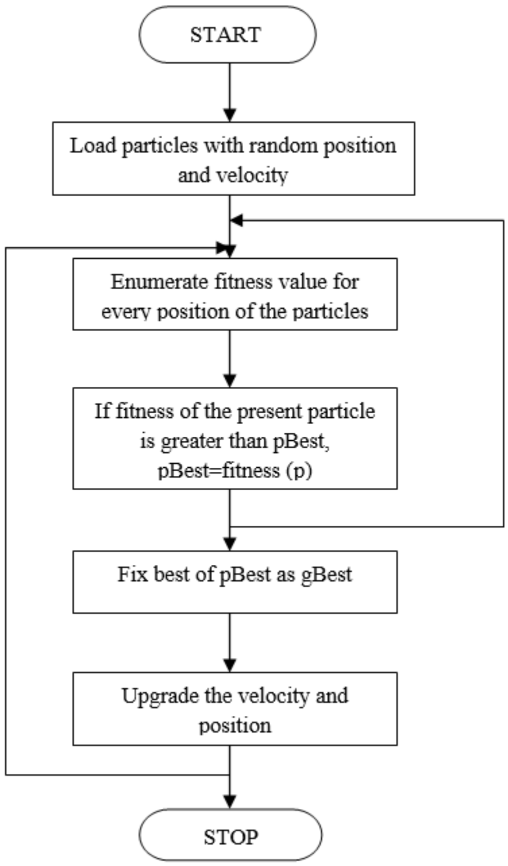

Fig.1. Flowchart of PSO algorithm

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.

IV. 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 [10]. 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.

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 ∈ 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.

V. 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 optimisation outlook for the global optimisation problem [11]. 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, which are [12]:

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,

$$\frac{dXi}{dt} = N_i + F_i + D_i \tag{3}$$

A. 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 [12]:

$$N_i^{new} = N^{max} \propto_i + \omega_n N_i^{old} \tag{4}$$

$$\propto_i = \propto_i^{local} + \propto_i^{target} \tag{5}$$

where 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 [12]:

$$\propto_i^{local} = \sum_{j=1}^{NN} \widehat{K}_{ij} \widehat{X}_{ij} \tag{6}$$

$$\widehat{X}_{ij} = \frac{X_j - X_i}{\|X_j - X_i\| + \varepsilon} \tag{7}$$

$$\widehat{K}_{ij} = \frac{K_i - K_j}{K^{worst} - K^{best}} \tag{8}$$

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

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

$$\propto_i^{target} = C^{best} \widehat{K}_{i,best} \widehat{X}_{i,best} \tag{9}$$

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}.

B. 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:

$$F_i = V_f \beta_i + \omega_f F_i^{old} \tag{10}$$

where,

$$\beta_i = \beta_i^{food} + \beta_i^{best} \tag{11}$$

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 food i^{th} krill best fitness outcome is established in the population till date is implied as β_i^{best}.

C. Physical diffusion

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:

$$D_i = D^{max} \delta \tag{12}$$

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

VI. RESULTS AND DISCUSSIONS

The Figs. 2, 3, 4, 5 and 6 respectively present the visual representation of the improved quasi lossless FIC technique using PSO algorithm, FPA and KH algorithm. The below figures display the input images, decoded images using PSO, FPA and KH.

The decompressed KH images give better quality which is close to original input images compared to decompressed PSO and FPA images. The KH algorithm when applied to quasi lossless fractal image compression method works better slightly better than FPA.

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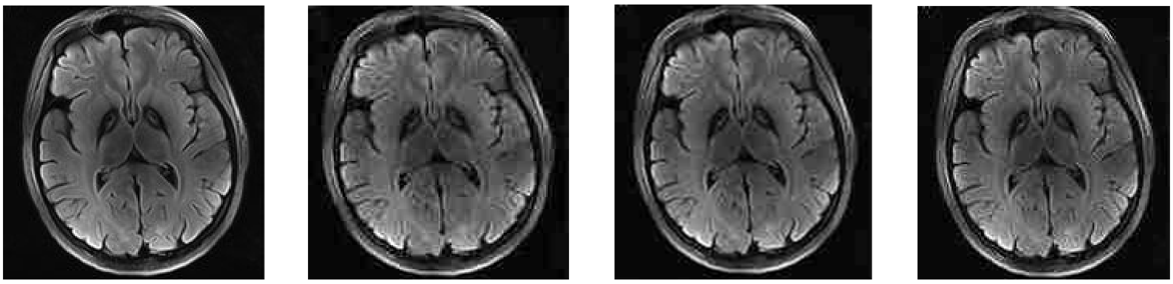

Fig. 2(a) Original MR image1 (b) Decompressed MR image1 using PSO (c) Decompressed MR image1 using FPA (d) Decompressed MR image1 using KH

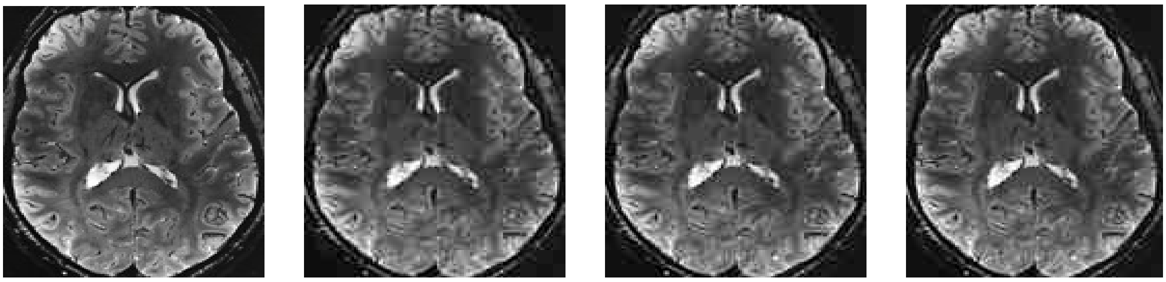

Fig. 3(a) Original MR image2 (b) Decompressed MR image2 using PSO (c) Decompressed MR image2 using FPA (d) Decompressed MR image2 using KH

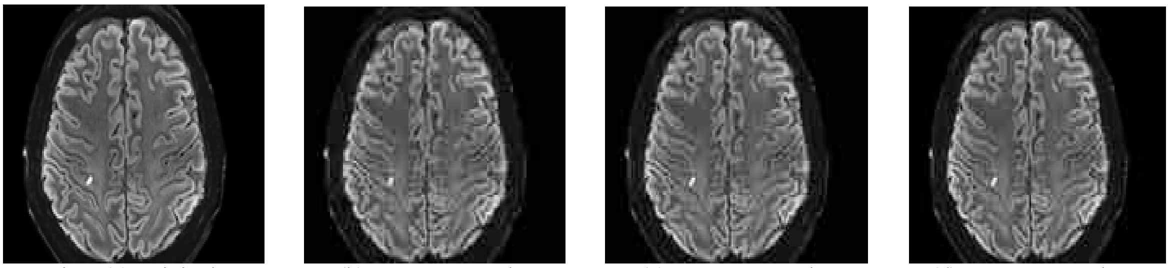

Fig. 4(a) Original MR image3 (b) Decompressed MR image3 using PSO (c) Decompressed MR image3 using FPA (d) Decompressed MR image3 using KH

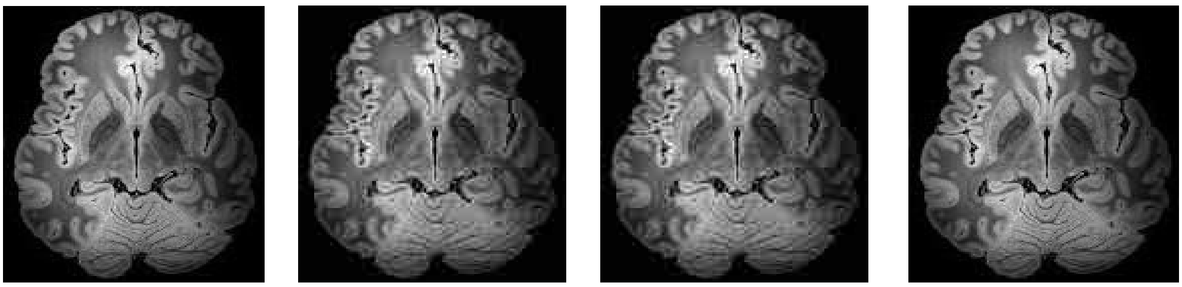

Fig. 5 (a) Original MR image4 (b) Decompressed MR image 4 using PSO (c) Decompressed MR image4 using FPA (d) Decompressed MR image4 using KH

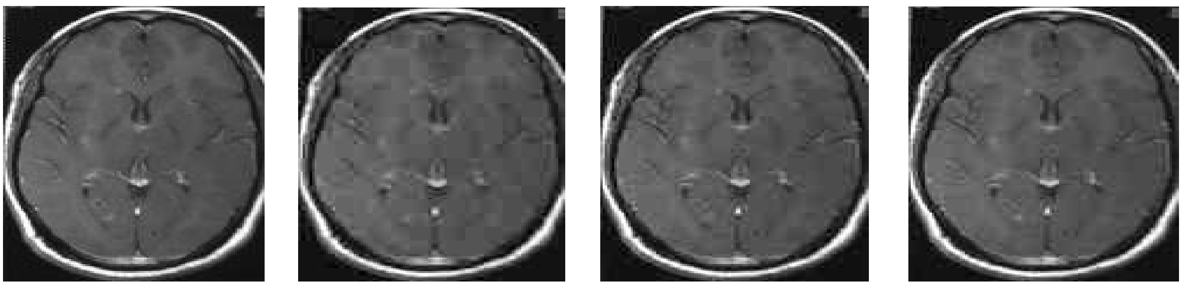

Fig. 6 (a) Original MR image5 (b) Decompressed MR image5 using PSO (c) Decompressed MR image5 using FPA (d) Decompressed MR image5 using KH

Table I Comparison results of 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	20	100	23.65765498	43.60766628	32.56861469	6.75320965
	FPA	20	100	26.98478675	39.28676929	27.83732890	7.73587540
	KH	20	100	27.54879856	36.68159899	27.54124897	7.95784235
MR Image2	PSO	20	100	21.58783689	42.39756998	30.54652600	6.55794139
	FPA	20	100	25.36790898	38.20754566	25.56577432	7.72581430
	KH	20	100	25.89124656	37.75890991	24.93688215	7.87359328
MR Image3	PSO	20	100	26.59000234	44.83909821	35.77672690	7.72573971
	FPA	20	100	28.74914345	39.75989888	29.81247210	8.65517280
	KH	20	100	29.25768990	39.23655423	29.32889135	8.78081469
MR Image4	PSO	20	100	25.26787957	42.59683980	34.85432086	7.65793390
	FPA	20	100	29.50972444	38.83891234	31.09559713	8.28546377
	KH	20	100	29.96642431	38.35354216	30.56693904	8.42812095
MR Image5	PSO	20	100	27.62676560	46.57894812	36.69588301	7.99680064
	FPA	20	100	29.57637889	41.63703183	32.32897054	8.74753180
	KH	20	100	29.98145877	41.28672190	31.81546012	9.01639330

Table I shows that the implementation of Krill Herd algorithm to quasi lossless fractal image compression is compared with other optimization techniques like PSO and FPA in terms of parameters such as PSNR, CT, DT and CR. Increased PSNR values and compression ratios implies that KH works better compared to other algorithms retaining quality of reconstructed image. Using KH technique, time taken for encoding and decoding medical images is also less compared to other algorithms.

VII. CONCLUSION

The efficiency of this Krill Herd approach to quasi lossless fractal image compression is rationalized with a set of different magnetic resonance images. This KH algorithm indeed produces good compression performance, while retaining the quality of the decompressed images. In this work, KH algorithm is implemented to quasi lossless FIC to reduce the time taken for compression and to maintain the decompressed images quality without any degradation. Experiment results show that the KH algorithm speeds up the quasi-lossless FIC technique to compress the different MR images more accurately, and it also outperforms the other algorithms like PSO and FPA concerning computation time, PSNR value and compression ratio.

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