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APPLICATION OF KRILL HERD ALGORITHM TO STANDARD FRACTAL IMAGE COMPRESSION

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ABSTRACT

Recently, image compression techniques have become mandatory with the instant growth of multimedia applications. Coherent diffusion and conservation of digital data gives the major goal for image compression technique. Pictures in digital format are always larger in size and its data transfer rate is usually very low which results in need of more storage space and transmission time. Without data compression and image compression, it will be impossible to store all those data and image files. Amidst different types of image compression approaches standard fractal image compression is a propitious method for rigid storing of images. It attempts to produce the result adequate to the original image quality. Standard fractal image compression operates very well and it gives a greater performance in producing an approximation that is nearer to the original image at higher compression ratios. However, it is a lossy method since it takes much time for encoding. To overcome the time taken for encoding and for better image compression, nowadays several new Meta heuristic optimization algorithms has been used. This work focuses on the implementation of the Krill Herd algorithm in standard fractal image compression. Krill Herd algorithm follows the concept of Simulation of herd attitude of krill throngs to search natural food. It is collated with Particle Swarm Optimization and Flower Pollination algorithms which are applied to standard fractal image compression. Krill Herd algorithm proves to be better compared to other algorithms thus by decreasing time taken for encoding and produces output image with less distortion. Outcomes are analysed based on good compression ratio and Peak Signal to Noise Ratio value.

Keywords: standard fractal image compression, krill herd algorithm, encoding, compression ratio.

INTRODUCTION

Usually, an image of large or regular size requires certain storage space and takes several minutes for transmission, thus needing a high speed internet service. But, if the image is compressed at specific compression ratio, the storage necessity is reduced and the transmission time is dropped. Time taken to transfer some compressed images to a disk is very little compared to send one uncompressed original file over internet [1]. With technological advancements in inter media applications, large image files becomes a prime obstruction within systems. Image compression is an advancement of data compression. It aims at minimizing image the repetition as well as saving and communicating image in a proficient manner. Digital Image Compression technique compresses and minimizes the size of images using different algorithms and standards. Lossless compression and Lossy compression are two common digital image compression techniques. Various types of algorithms are applied to compression schemes. Different kinds of compression approaches are developed recently. One such technique is fractal image compression (FIC). It depends on the attribute named self-similarity [2, 3]. A Fractal is a segmented geometric shape which is split into fragments; everyone is a diminished area replica of the entire part. In this paper, Standard Fractal Image Compression technique is exploited. Out of various image compression schemes, Standard Fractal Image Compression technique is one of the demanding approaches since it gives high compression ratio. However it suffers from large time taken for encoding. The major factor in FIC research is to decrease the compression time without any loss of quality. In recent years, many researchers have been done on fractal image compression. Many optimization algorithms like Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Flower Pollination Algorithm (FPA), etc. were introduced and used to boost up the Fractal Image Compression. PSO algorithm used here focuses on diminishing fractal encoding process. It produces lower error values compared to other algorithms, but it fails to obtain best solution for composite problems. So, when PSO is applied to images, quality of decoded image is low. To overcome this problem, the nature inspired Flower Pollination Algorithm proposed by Xin-She Yang is implemented to standard FIC. This optimization technique reduces the encoding time, but fails to maintain preserve the original image quality. Krill Herd (KH) algorithm is another type of bionic swarm intelligent algorithm rests on the simulation of Antarctic krill group's movement in the marine environment. It is a global probabilistic searching algorithm with simple operation, strong commonality, parallel processing strong robustness, largely applied to overcome the numerical function optimization problem and data clustering, the inverse radiation problem, the phase equilibrium calculation, the power flow optimization, etc.

In the present work, Krill Herd (KH) algorithm is compared with PSO and FPA. This paper showcases how the execution of Krill Herd algorithm to standard FIC is finer contrast to other algorithms.

STANDARD FRACTAL IMAGE COMPRESSION

Analytically z = f(x, y) interprets two dimensional image. In image at point (x, y), f(x, y) stands

for the gray level, 0 indicates black and 1 is for white. Close Interval [0 1] signifies I. When transformation W is enforced on the image f, a transformed Image W (f) is formed. Usually, transformation pulls points nearer jointly as it shrinks. Compositions of rotations, scaling, reflections and translations form affine transformations. Generally, affine transformation is specified as:

$$W = \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} a & b \\ c & d \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} + \begin{bmatrix} e \\ f \end{bmatrix} = \begin{bmatrix} ax + & by + & e \\ cx + & dy + & f \end{bmatrix} \quad (1)$$

To calculate the coefficients, priorly the translations (e & f), scaling factors(r & s) and rotations (θ & φ) should be investigated. To compress grayscale images of three dimensional size with x & y coordinates and intensity as z, the transformation looks appropriate. Equation 2 denotes the transformation with s_i reigning the contrast and $o_i$reigning the brightness [4].

$$w_i \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} a_i & b_i & 0 \\ c_i & d_i & 0 \\ 0 & 0 & s_i \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} + \begin{bmatrix} e_i \\ f_i \\ o_i \end{bmatrix} \quad (2)$$

Compression and Decompression of Images

Transformation is based on contractive mapping fixed theorem concept. It asserts, once transformation diminishes and used often in primary point, it gathers to a distinctive fixed point. X is a complex metric space, W: X->X is constrictive at that time unique fixed point IWI will be W. Image is nothing but a group of transformations. Image denoted by f is segregated into parts by compression operation and transformation w_i is carried on to recover the input image. D_i specifies input image part and w_i is carried on D_i. v_i specifies the splitted area of the input image, denotingv_i (D_i)=R_i (Range blocks). Therefore UR_i=I^2 with $R_i \cap R_j$ when i ≠ j. As long as 'f' indicates image, W implies transformation, the transformed image is specified as f=W (f) =w_1 (f) U w_2 (f) U w_3 (f)…….U w_n (f). Fusion of w_i (f) is interpreted by the map W to acquire transformed domain, where w_i = D_i× I. Differentiation of transformed and the range block is carried out to find range. If both are equivalent, then it is replicated as Range. D_i is found and mapped with w_i, if w_i is employed to the piece of the image above D_i, several sections are discovered to be extinct in R_i. Compression operation relies on the complication of locating pieces of R_i (corresponding to D_i).

Standard fractal compression algorithm:

a) Stack an input image into buffer.
b) Segregate the image into with non-overlap square blocks.
c) Pick the initial level of the domain block to be two times the level of the range block.
d) Down sample domain blocks equal to the level of range blocks and then for each block enumerate the eight possible feasible affine transformations.
e) Specify the domain block similar to the range block in accordance to some metric and calculate the compression criterions that serves mapping.
f) Reserve the coefficients that constitutes fractal element.

Standard fractal decompression algorithm:

a) Stack the initial image to decompress.
b) Employ w_i frequentlytill fixed point is gathered, for every w_i identify domain block and resize to the range block level.
c) Increase the pixel values using s_i and add up o_i thencalculate the pixel values in each R_i, to replicate the domain block information to the range blocks.
d) Consider the output of first recurrent as the input of the next recurrent.
e) Return the process till strong feature is obtained.

Simple decompression operation is the one main remarkable feature of fractal image compression. The decompress or performs similar to the traditional compressor. Time taken for decompression is less in contrast to time taken for compression of images.

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]. 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 where as selected particles numbers are nothing but swarm range by primary pressured solutions [6]. Every particle is loaded based on personal best and global best at that each and every particle 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 [7].

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

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

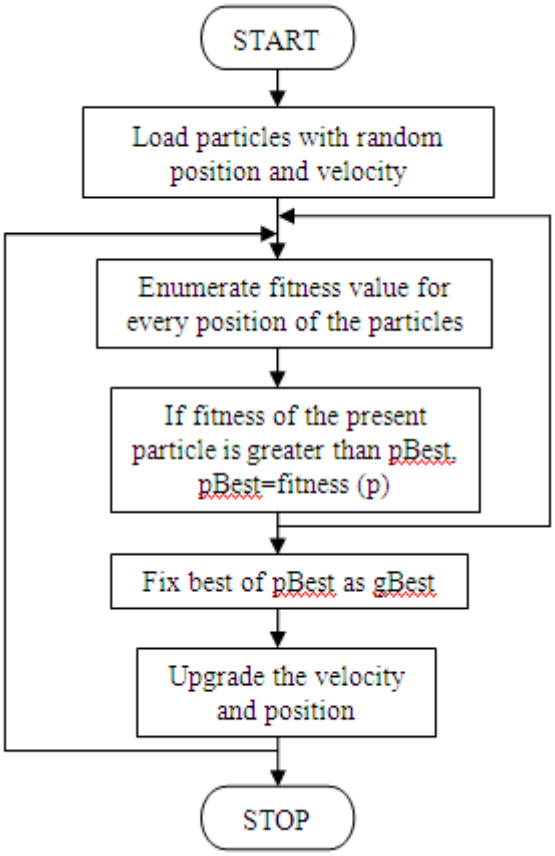
In t^{th} iteration, V_i^t is the velocity and X_i^t refers to i^{th} particle position. P_i denotes i^{th} particle pBest. At t^{th} iteration indicates gBest. K_1 as well K_2 specifies speed elements with value 2. With interval [0, 1] rand () refers random function. The fitness function is defined based on equation (3).Threshold value is determined based on the maximum fitness value given by function. The fitness function is,

f (t)=F0+F1 (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.

PSO Flowchart



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 [8, 9]. 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 acts 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 [10, 11].

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 pollination.

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.

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. In KH, the location of food and each krill throngs or individuals position and its minimum distance are regarded as objective function [12, 13]. Optimization procedure of KH is based on three steps, which are:

a) Movement induced by other krill individuals (N_i);
b) Foraging activity (F_i);
c) Random diffusion (D_i).

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

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

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:

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

where

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

and N^{max} refers to maximum actuated speed, inertia weight in [0, 1] is denoted by ω_n, N_i^{old} 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:

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

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

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

where K^{worst} and K^{best}accordingly are krill's best and worst fitness. K_i stands for 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:

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

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

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 ith 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 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}.

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:

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

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

RESULTS AND DISCUSSIONS

Here in this work, the Krill Herd algorithm is employed to standard fractal image compression technique as well as it is compared with PSO and FPA. PSO is a one-way information sharing mechanism. PSO algorithm 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 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. Krill Herd algorithm is used to get over these problems. KH algorithm obtains good results. KH performs slightly better than FPA algorithm because it produced good results for all the images applied without any loss of information.

The original images, compressed images and decompressed images using PSO, FPA and KH are displayed in the Figures 6.1, 6.2, 6.3, 6.4 and 6.5. The above figures shows that decompressed KH images has better visual quality than decompressed PSO and FPA

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images. The number of iterations taken here is 20. The size of the population is always fixed in every meta-heuristic approach. Other algorithms gives near optimal solutions whereas KH based compressed image is proximate to real one and discards the image distortion within standard FIC. The results are validated by using standard compression criterions such as Peak Signal to Noise Ratio (PSNR), Compression Ratio (CR) and Compression Time (CT).

Simulation results shows that the KH algorithm produces a very good PSNR values, compression time and compression ratio for the above five different images 6.1, 6.2, 6.3, 6.4 and 6.5.

Figure-6.1(a) Original image1.

(b) Decompressed image1using PSO.

(c) Decompressed image1 using FPA.

(d) Decompressed image1 using KH.

Figure-6.2 (a) Original Image2.

(b) Decompressed image2 using PSO.

(c) Decompressed image2 using FPA.

(d) Decompressed image2 using KH.

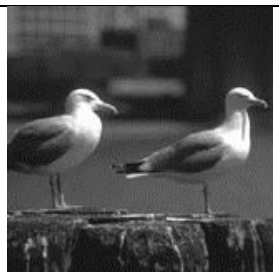
Figure-6.3 (a) Original image3.

(b) Decompressed image3 using PSO.

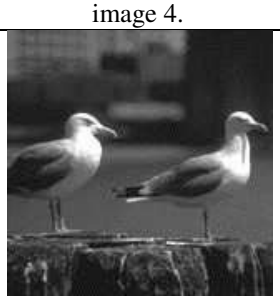
(c) Decompressed image3 using FPA.

(d) Decompressed image3 using KH.

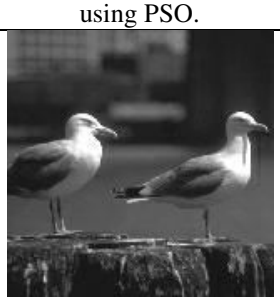
Figure-6.4 (a) Original image 4.



(b) Decompressed image4 using PSO.



(c) Decompressed image4 using FPA.



(d) Decompressed image4 using KH.

Figure-6.5 (a) Original Image5.

(b) Decompressed image5 using PSO.

(c) Decompressed image5 using FPA.

(d) Decompressed image5 using KH.

Table-1. Comparison results of standard fractal image compression using PSO, FPA and KH for five different images.

Images	Algorithm	Population size	Iteration	PSNR	Compression time (s)	Decompression time (s)	Compression ratio
Image1	PSO	20	100	25.25376210	55.46344994	37.14666846	7.41788843
	FPA	20	100	27.14728996	49.24307866	32.01777932	9.32675831
	KH	20	100	28.23556401	48.39800031	30.95899947	10.18739945
Image2	PSO	20	100	23.41855564	50.02440675	36.44000981	6.89257896
	FPA	20	100	26.57990546	42.17861130	27.96778234	10.31092353
	KH	20	100	27.25880412	41.65600489	26.55503215	10.63935648
Image3	PSO	20	100	28.56070856	58.13990300	38.47833305	8.15553765
	FPA	20	100	31.34576099	52.46785889	32.04311789	10.02224591
	KH	20	100	32.08976567	51.54676734	31.02677445	10.42145673
Image4	PSO	20	100	27.84456230	57.54335678	37.33489899	8.01133487
	FPA	20	100	30.54767022	51.89987659	31.45780865	9.98670982
	KH	20	100	31.07946683	51.06665823	30.67451287	10.46778671
Image5	PSO	20	100	28.83544700	58.34779190	38.63679923	8.98564342
	FPA	20	100	33.21768221	53.67563321	33.27669541	10.24108231
	KH	20	100	33.85664880	53.06611224	32.98890768	10.57732872

The above result proves that the accuracy and speed performance of KH is better than PSO and FPA.

The increased PSNR value and high compression ratio indicates that KH performs better than other algorithms. In standard fractal image compression technique, encoding time is minimized using KH which specifies its efficiency. Thus, KH is simple, stable and efficient in providing global optimal solution when compared to PSO and FPA.

CONCLUSIONS

All the three algorithms discussed in this paper are swarm intelligence based algorithm which proved to be better for all engineering problems both practically and theoretically. Here, KH algorithm is used to boost up fractal image compression and it works better compared to PSO and FPA. This image compression algorithm is very effective, when it comes to compression ratio and compression time and also, it maintains the quality of image in terms of better PSNR value.

The Krill Herd algorithm is easy, user friendly, adaptable and more promptly preferable to solve optimization problems. It can be applied to all type of maximization or minimization problems. Tabulation results indicates that KH is very proficient compared to FPA and PSO. i.e. The increased PSNR value shows that KH works finer. The KH based standard fractal image compression technique decreases time, upgrades the outcomes. Its effect is increased contrast to other different optimization techniques. Nevertheless, some form of trial-and-error tuning is always needed for each and every particular case of optimization problem. In further work, application of KH algorithm can be proposed for various fractal image compression techniques.

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