APPLICATION OF KRILL HERD ALGORITHM TO STANDARD FRACIAL 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 applications. Coherent diffusion and conservation of digital data gives the major goal for image compression technique. Decreasing time taken for encoding and produces output image with less distortion. Outcomes are analysed based on good 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 FRACIAL 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:

\[
W = \begin{bmatrix} \alpha & \beta & 0 \\ \gamma & \delta & 0 \\ \epsilon & \zeta & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} + \begin{bmatrix} a \\ b \\ c \end{bmatrix} = \begin{bmatrix} \alpha x + \beta y + \epsilon \\ \gamma x + \delta y + \zeta \\ c \end{bmatrix}
\]  

(1)

To calculate the coefficients, priorly the translations (ε & ζ), scaling factors (ρ & σ) 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].

\[
w_i = \begin{bmatrix} a_i & b_i & 0 \\ c_i & d_i & 0 \\ 0 & 0 & s_i \end{bmatrix} \begin{bmatrix} x_i \\ y_i \\ z_i \end{bmatrix} + \begin{bmatrix} e_i \\ f_i \\ 0 \end{bmatrix}
\]  

(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 constructive 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, denoting \( \mathcal{V}_i \) \( \mathcal{D}_i = \mathcal{R}_i \) (Range blocks). Therefore \( \mathcal{W} = \mathcal{I}^2 \) with \( \mathcal{R}_i \cap \mathcal{R}_j \) when \( i \neq j \). As long as ‘f’ indicates image, W implies transformation, the transformed image is specified as \( f = W(f) = w_1(f) \cup w_2(f) \cup w_3(f) \cup w_4(f) \cup w_5(f) \cup w_6(f) \cup w_7(f) \cup w_8(f) \). Fusion of \( w_i(f) \) is interpreted by the map W to acquire transformed domain, where \( w_i = D_i \times I \). 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 \( \mathcal{R}_i \). Compression operation relies on the complication of locating pieces of \( \mathcal{R}_i \) (corresponding to \( \mathcal{D}_i \)).

Standard fractal compression algorithm:

a) Stack the initial image to buffer.

b) Segregate the image into 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 \( w_i \) frequently till 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 \( o_i \) then calculate 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 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 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].

\[
V_i^{t+1} = V_i^t + K_1 \cdot r \cdot (P_i - V_i^t) + K_2 \cdot r \cdot (G^t - X_i^t)
\]

(1)

\[
X_i^{t+1} = X_i^t + V_i^{t+1}
\]

(2)

In \( t^{th} \) iteration, \( V_i^t \) is the velocity and \( X_i^t \) refers to \( t^{th} \) particle position. \( P_i \) denotes \( t^{th} \) 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,

\[ f(x) \text{ denotes minimum or maximum objective, where } x = (x_1, x_2, \ldots, x_d) \]

Format ‘n’ number of flowers population using arbitrary results

Obtain \( g^* \), the best solution within primary population 

While \( t < \text{Max Generation} \)

for \( i = 1 : n \)

if \( \text{rand} \) is less than switch probability 

Sketch \( \text{L} \) from a Levy distribution

Global pollination over 

\[ X_i^{t+1} = X_i^t + \gamma L (g^* - X_i^t), \]

else

Outline \( \xi \) out of a uniform distribution in [0, 1]

Execute local pollination over 

\[ X_i^{t+1} = X_i^t + \xi (X_j^t - X_k^t), \]

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 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,

$$\frac{dx_i}{dt} = N_i + F_i + D_i$$  \hspace{1cm} (1)

**Movement induced by other krill individuals ($N_i$)**

The movement direction $\alpha_i$ 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:

$$N_i^{new} = N_i^{max} \alpha_i + \omega_n N_i^{old}$$ \hspace{1cm} (2)

where

$$\alpha_i = \alpha_i^{local} + \alpha_i^{target}$$ \hspace{1cm} (3)

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

$$\alpha_i^{local} = \sum_{j=1}^{NN} R_{ij} \hat{X}_{ij}$$ \hspace{1cm} (4)

$$\hat{X}_{ij} = \frac{X_j - X_i}{K_{worst}}$$ \hspace{1cm} (5)

$$R_{ij} = \frac{K_{i} - K_{j}}{K_{worst} - K_{best}}$$ \hspace{1cm} (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, $K_i$ exemplifies $j^{th}$ ($j = 1, 2, \ldots, NN$) neighbour fitness; the allied positions are denoted as $X_i$ and the number of the neighbours is symbolized as $NN$. Furthermore, $\alpha_i^{target}$ can be written as:

$$\alpha_i^{target} = C^{best} \hat{R}_{i, best} \hat{X}_{i, best}$$ \hspace{1cm} (7)

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

**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:

$$F_i = V_f \beta_i + \omega_f F_i^{old}$$ \hspace{1cm} (8)

Where,

$$\beta_i = \beta_i^{food} + \beta_i^{best}$$ \hspace{1cm} (9)

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

**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:

$$D_i = D^{max} \delta$$ \hspace{1cm} (10)

Where $D^{max}$ denotes the maximum speed of diffusion, and $\delta$ 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.
images. The number of iterations taken here is 20. The size of the population is always fixed in every meta-heuristic approach. Other algorithms give 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 show 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.
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.
REFERENCES


