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AN IMPROVED HARMONY SEARCH ALGORITHM FOR REDUCING COMPUTATIONAL TIME OF FRACTAL IMAGE CODING

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ABSTRACT

Fractal image coding (FIC) based on the inverse problem of an iterated function system plays an essential role in several areas of computer graphics and in many other interesting applications. FIC received considerable attention because of its high resolution, fast decoding, and many other advantages. However, the method has not been used widely because it required high computation time in the encoding process, which is one of its drawbacks. Many optimization methods are introduced to serve in solving this drawback and reducing the searching time for optimal solution. The approach that based on meta-heuristic methods is promising, which employ some degree of randomness to search for an optimal solution. This study introduces the harmony search algorithm to improve the FIC technique. The algorithm searches for an optimum solution while playing music. Finding music harmony has been proven to solve optimization problems by searching for an optimal solution. This algorithm is naturally inspired and is currently in demand. The experiments show that, compared with other techniques, the proposed method has excellent performance in image quality and reduces the computation time and storage space.

Keywords— *Fractal, iterated function system (IFS), fractal inverse problem, fractal image compression (FIC), harmony search algorithm (HAS).*

1. INTRODUCTION

In 1988, the concept of fractal coding was firstly introduced by Barnsley et al. [1], when they were tried to find the IFS of an image, such that if these system of function are iterated they approximate the given image as an attractor. This theory is then improved in 1992 by Barnsley's student, Jacquin [2]. He introduced the concept of fractal image coding and interested in studying of partitioned iterated function system. Jacquin approach has been popularized practically and theoretically by several researchers, as soon as he published his technique. Nevertheless, none of these attempts was proven to be efficient. Therefore, many efforts are highlighted towards employing of evaluative algorithms. The optimization models have been proposed to represent a normal evolution mechanism. Several real world problems are considered as optimization problems, therefore, a developed method is required to increase their efficiency and productivity in order to search for optimal solution. Some degree of randomness should be added and this is possible by using meta-heuristic methods. They are considered as attempts to approximate best solution and increase the efficiency. Some of these methods are nature inventor [3]. The harmony search algorithm (HSA) is a metaheuristic algorithm used to solve optimization problems [4]. The method has been applied to solve different kinds of problems in the past years and provided effective results compared with other metaheuristic algorithms and conventional techniques, which are computationally costly. The remainder of this paper is organized as follows: Some literatures review is presented in Section 2. Section 3 introduced some of the important fractal terminologies to understand the FIC technique. Section 4 presents some of the metaheuristic optimization algorithms to improve the proposed technique. Section 5 discusses the implementation of the proposed algorithm with some experiments and comparisons. Section 6 summarizes the conclusions.

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2. LITERATURE REVIEW

After introducing of genetic algorithm (GA) approach by Goldberg [5], it is used to solve some of the optimization problem in a large search space with different optima, and hence, several interesting applications are based on. The use of this approach in fractal image coding started in 1995, when Jacques et al. [6] introduced a genetic programming method which is investigated in solving the general inverse problem and perform at the same time a numeric and symbolic optimization. In 1997, Vences and Rudomin [7] used genetic algorithms (GAs) to find a partial iterated function system (PIFS) which encodes a single image. They did this work by reducing the needed time to achieve process in about 30% compared with Barnesly's [8]. In 2000, Dasgupta et al. [9] introduced the effectiveness of an evolutionary algorithm to obtain the IFS code in black and white images. In their work, the IFS is a set of maps that can be represented as a set of real parameters. In 2000, Wang, Zhang, and Yu [10] used the fractal technique to encode a part of the image and employed other algorithms to the remaining part. They proposed a new image space mapping, which is called the partial fractal mapping. In 2006, Mohamed and Aoued [11] presented the solution to the fractal inverse problem using GA. Moreover, they designed a fractal compression algorithm to search in the domain block based on GA. They applied the standard Barnsley algorithm [8] and the Y. Fisher algorithm [12], and the results were compared with the results of their work to prove the efficiency of their method. In 2006, Bouboulis et al. [13] introduced an image compression program employing fractal interpolation surfaces that are attractors of some local iterated function systems (LIFS). They attempted to improve the fractal image compression by replacing the contraction constant by the contraction function that provides a flexible construction. Therefore, the number of regions and domains in the image coding can be reduced, and the quality of the decoded image can be improved. In 2010, Lon Lin [14] introduced similar measures for fractal image compression that are resistant to noises. He proposed the integration of the robust estimation technique from statistics into the encoding process of the fractal inverse problem to obtain the parameters. However, the main drawback of the robust FIC is high cost. He tried to overcome this drawback by using the particle swarm optimization (PSO) technique that is used to decrease the search time. In 2014, Nadira et al. [15] improved the iterated fractal algorithm by designing an efficient search of the domain pools for color image compression using GA. They obtained a decreased coding time and intensive computation works. In 2016, Al-Bundi et al. [16] proposed the crowding optimization method to improve the FIC technique. They proved that their method performed better than the other evolutionary optimization methods.

HSA is employed in the present study. The algorithm was proposed in 2001 by Geem et al. [17] as one of the optimization algorithms. They noticed the resemblances among the music improvisation methods and formed an optimal solution to difficult problems. The better harmony vector replaces the worst harmony vector in a harmony memory (HM). HSA proved its efficiency and effectiveness in various studies [3, 18]. In 2012, El-Satawy and Ahmed [19] introduced a new multi-objective evolutionary method. The new technique merges harmony search optimization with chaos search. In 2013, Jiaqi Di and Nihong Wang [20] proposed a new HSA with chaos. The proposed algorithm initialized and developed HSA with the chaos optimization algorithm depending on the secondary carrier wave, which improved the optimization accuracy and convergence rate. In 2014, Osama Abdel-Raoufet et al. [21] improved the HSA to solve linear assignment problems. Their proposed method, which was based on the chaotic behavior of a caustic monophony, was used to generate solutions. In 2014, Osama Abdel-Raouf et al. [22] proposed a novel hybrid optimization technique called the improved flower pollination algorithm using chaotic harmony search. In 2015, Gao et al. [23] described the classical harmony algorithm and its basic applications. They presented, discussed, and applied the use of the modified algorithm to improve the performance of wind generators. In the present work, HSA is used to improve the encoding time of the FIC technique. This improvement is used in one of the important application, image retrieval [24], the result was promising. In 2017, Al-Saidi et al. is also improved fractal image coding based in their approach on block complexity [25].

3. FRACTALS IMAGE CODING

Barnsley [26] encoded computer graphics by using the IFS and obtained a 1,000:1 compression ratio. This result encouraged his student Jacquin to propose a new coding method by partitioning the given image into blocks. This approach gained extensive interest because of its novelty, high compression ratio with good resolution, and fast decoding.

3.1 Basic Terminology

The IFS theory is important in the fractal field and is a powerful tool to search for fractals. The theory is applied in generating and modeling irregular patterns and can be viewed as image compression when associated with the automatic generation of fractal and irregular forms. In both applications, the generated information is called the attractor of the IFS. Works on contractive mappings to produce fractal sets have been considered by many researchers. Moreover, most fractal image compression methods are based on the IFS.

The IFS was developed by Hutchison [27] and Barnsley et al. [1, 7,26, 28]. These systems of mapping were widely discussed and used in many applications, such as in the image compression method. The mathematical definition of the IFS is expressed as:

In the collage theorem, a set of transformations $w_n, n = 1,2,\dots,N$ must be obtained so that the union or collage of the transformations is close to the given set L to obtain an IFS with attractor that is "close to" a set.

With the rapid development of multimedia technology, the need for digital images is rapidly growing. Managing these resources effectively has become a focus of many studies. Considerable attention was focused on fractal geometry because of its ability to describe natural phenomena qualitatively and quantitatively. Fractal is an image that represents the attractor generated by the interpolation method, that is, IFS. Some natural images are not globally self-similar; they contain local self-similarity. In this case, the LIFS is introduced to describe such types of images. Iterated Function System (IFS) is developed by Hutchison (1981) [27], Barnsley and others (1985, 1986, 1988) [1-7-26-28]. These systems of mapping were discussed widely and used in many applications, such as image compression method. The mathematical definition of the *IFS* is given as follows:

Definition 1: Let (*X*, *d*) be a complete metric space. a finite set of contractive mappings $w_i: X \to X$ with contractivity factors s_i for $i = 1,2,\dots,N$ such that $s = \max\{s_i, i = 1,2,\dots,N\}$ is called the IFS on *X*.

IFS is based on the affine transformation given by:-

$$w(x) = w\begin{pmatrix} x \\ y \end{pmatrix} = \begin{pmatrix} r_1 \cos\theta_1 & -r_2 \sin\theta_2 \\ r_1 \sin\theta_1 & r_2 \cos\theta_2 \end{pmatrix}\begin{pmatrix} x \\ y \end{pmatrix} + \begin{pmatrix} e \\ f \end{pmatrix} \quad \dots (1)$$

Sometimes, the world (hyperbolic) is used with the iterated function systems, and it sometimes drops in practices. The following theorem will show why we use the concept of hyperbolic *IFS*.

Theorem 1: (Fixed point theorem) Let (X, d) be a metric space, let $\{w_1, w_2, \dots w_N\}$ be a hyperbolic iterated function system where $w_i, i = 1,\dots,N$ is a contraction mapping. Let $W: H(X) \to H(X)$ is defined by:

$$W(B) = \cup_{n=1}^{n} w_n(B) \quad \dots (2)$$

Then W is a contraction mapping with contractivity factor s on the complete metric space $(H(X), h(d))$.

That is mean $h(W(B), W(C)) \leq s \cdot h(B, C)$ for all $B, C \in H(X)$.

Let $A \in H(X)$ be defined as;

$$A = W(A) = W^n(A)$$

Then A is a unique fixed point such that;

$$A = \lim_{n\to\infty} W^n(B) \quad \text{for any } B \in H(X)$$

Definition 2: In *IFS*, any compact subset (fixed point) $A \in H(X)$ is called attractor for *IFS* if;

$$A = \cup_{n=1}^{n} w_n(A)$$

The fixed point observes existence and uniqueness by the contraction mapping theorem. An important property of any *IFS* is the attractor, that means the attractor A is fully known by the set of coefficients of W, and can be generated by applying the *IFS* to any starting point several times.

Theorem 2: The Collage Theorem [26]

Let (X, d) be a complete metric space. Let $\{X; w_n, n = 1,2,\dots,N\}$ be an *IFS* with contractivity factor s, $0 \leq s < 1$ and let L be a closed subset of X such that:

$$h(L, \cup_{n=1}^{N} w_n(L)) < \epsilon \quad \dots (3)$$

for some $\epsilon > 0$, where h is the Hausdorff distance. Then

$$h(L, A) \leq \frac{\epsilon}{1-s}$$

for the attractor A of the *IFS*'s.

In the collage theorem, a set of transformations $w_n, n = 1,2, \dots, N$ must be obtained so that the union or collage of the transformations is close to the given set L to obtain an IFS with attractor that is "close to" a set.

With the rapid development of multimedia technology, the need for digital images is rapidly growing. Managing these resources effectively has become a focus of many studies. Considerable attention was focused on fractal geometry because of its ability to describe natural phenomena qualitatively and quantitatively. Fractal is an image that represents the attractor generated by the interpolation method, that is, IFS. Some natural images are not globally self-similar; they contain local self-similarity. In this case, the LIFS is introduced to describe such types of images. A collection of all local transformations w_i is known as a PIFS w_i, $i = 1, 2, \dots, N$. Each w_i can be written as:

3.2 Jacquin Method for FIC [2]

The FIC is an important search area with a large number of possible application fields. The FIC determines the representative codes of any given object that is self-similar or contains different types of self-similarities. Barnsley [26] introduced this concept with the collage theorem. When the considered object is an image, fractal image compression is applied. A method has been proposed by Jacquin [2] to solve this kind of problem, which has been investigated by many authors. Compared with other methods, the FIC is time consuming in searching similar domain blocks. Therefore, the demand for a new technique to solve this problem and improve the speed of this method arises.

The problem can be easily solved when the given set is self-similar. In this case, the IFS can be easily found by transforming the self-similarity property. Barnsley [26] stated an approximated solution to the inverse problem of fractals using the IFS. This solution was verified in the collage theorem, which supplied the first step in solving fractal inverse problems.

This approach reduces the redundant area in the image. The process of transforming images to codes is complicated, but the reversing task is simple. The Jacquin approach is dependent on the IFS attractor, and obtaining the PIFS parameter is regarded as the main problem in fractal coding. The following is an explanation of the main processes of Jacquin technique:

1. A given image M is partitioned into non-overlapping blocks $R=\{R_1,R_2,\dots,R_m\}$ of size $r\times r$ called range blocks, where $m = (M/r)^2$, and overlapping blocks $D=\{D_1,D_2,\dots,D_n\}$ of size $2r\times 2r$ called domain blocks, where $n = (M-2r+1)^2$ as shown in Figure 1.

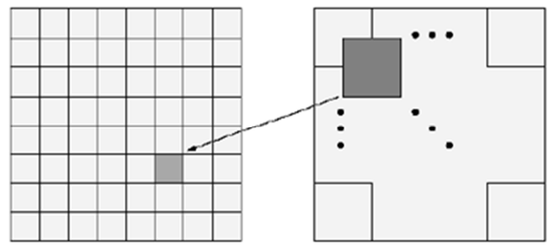

Figure 1(a,b): Domain and range blocks of the *PIFS*

2. For each range block R_i, choose its approximate domain D_k, $k=1,\dots,n$ and a suitable contractive affine transformation w_{ik} that satisfied the following:

$$d(R_i, w_{ik}(D_k)) = \min d(R_i, w_{ij}(D_j))$$

where w_{ik} is the contractive affine transformation from D_j to R_i. This can be represented by $d(R_i, w_{ij}(D_j))$ where d refers to the mean square error (MSE) between R_i and w_{ij} that consist of two mappings T_j and θ_{ij} such that: $w_{ij} = \theta_{ij} * T_j$, and hence, T_j represents the contraction transformation that transformed D_i size into R_i size. This transformation is described as follows:

The domain block D_j is divided into non-overlapping blocks of size 2×2, where the pixel value of the transformed block $T_j(D_j)$ is computed from the average of the four pixels in the block of D_j, as shown in Figure 2.

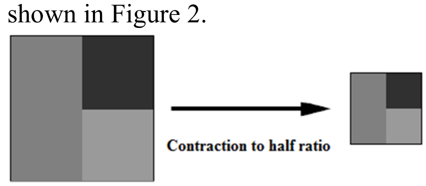

Figure 2: The contraction of a domain block.

The mapping θ_{ij} is performed in two steps; firstly, the block $T_j(D_j)$ is transformed using eight isometries given in Figure 3.

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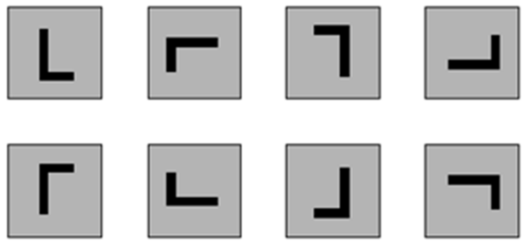

Figure 3: The eight isometries

Second step, the pixel values of the resulting block from first step is transformed by W_{ij}, where W_{ij} is defined as follows:

$$W_{ij}(z) = s_i z + o_i \quad \text{....(4)}$$

Here z represents the pixel value that obtained from the first step, and the scaling s_i and the offset o_i defined in (5) and (6) respectively, are calculated by the mean square error (*MSE*) of the pixel values of the range block R_i.

$$s = \frac{\left[n\sum_{i=1}^{n} a_i b_i - \sum_{i=1}^{n} a_i \sum_{i=1}^{n} b_i \right]}{\left[n\sum_{i=1}^{n} a_i^2 - \left(\sum_{i=1}^{n} a_i \right)^2 \right]} \quad \text{.... (5)}$$

$$o = \frac{1}{n}\left[\sum_{i=1}^{n} b_i - s\sum_{i=1}^{n} a_i \right] \quad \text{.... (6)}$$

The *MSE* difference is calculated using:

$$MSE = \frac{1}{n}\left[\begin{array}{l} \sum_{i=1}^{n} b_i^2 - s\left(s\sum_{i=1}^{n} a_i^2 - 2\sum_{i=1}^{n} a_i b_i + 2o\sum_{i=1}^{n} a_i \right) \\ + o\left(no - 2\sum_{i=1}^{n} b_i \right) \end{array} \right] \quad \text{.... (7)}$$

This representation contains two parts, namely, the massive part to represent the image pixels and the geometric part to represent the isometric and scaling.

4. METAHEURISTIC METHOD TO SOLVE FRACTAL IMAGE CODING

4.1 Swarm Method

Swarm algorithm is an optimization algorithm that generates the optimal or near-optimal solutions. Swarm algorithm was developed by Kemedy and Eberhert in 1995 [29]. The mechanism of this algorithm is based on the behavior of birds flocking at the same time seeking for food. The birds connect with each other when searching for food and reach their aim with minimal time. The method can be easily implemented and considered to be simpler than the other metaheuristic methods, such as the ant colony optimization algorithm. Compared with the GA, the size of the population in the swarm method is small, which leads to the initialization of the populations in the simplest manner. Thus, the swarm method is preferred over the other optimization algorithms. Swarm algorithm improves the general purpose and employs the concept of fitness.

The swarm population is initialized with random solutions called particles. Every particle can freely fly through the search process. Each particle is considered a point in k-dimensional space. The following equations represent the stoning step for the swarm algorithm.

$$v_{i,k}(t) = v_{i,k}(t-1) + a_1 r_1 \left(p_{i,k} - x_{i,k}(t-1) \right) + a_2 r_2 (p_k - x_{i.k}(t-1)) \quad \text{...(8)}$$

$$x_{i,k}(t) = x_{i,k}(t-1) + v_{i,k}(t) \quad \text{...(9)}$$

where $a_1, a_2 > 0$ and $r_1, r_2 \in (0,1)$ are random numbers, t is time, $\{x_{i,1}, x_{i,2}, \dots, x_{i,k}\}$ are the particles $\{p_{i,1}, p_{i,2}, \dots, p_{i,k}\}$ are the best positions (best fitness) of kth particles up to time $(t-1)$, and p_k is the best position among all populations (or among all swarms) up to time $(t-1)$.

First, the population size should be determined, and the position and velocity of the particles should be initialized. The movement of each particle depends on Eqs. (8) and (9), and the fitness function is calculated. Afterward, the best position of each particle and the swarm is record. Finally, the work ends when the criterion is satisfied. The best position of the swarm is the final solution [30].

Fractal Image Compression using Swarm Method

The FIC determines the best domain block identical to each rang block, but it takes a long time. The swarm method can provide faster encoding of the scale blocks. The method is based on the population to search for global optimum [20]. The PSO method is used to screen and remove the trivial domain blocks to reduce the amount of data in the encoding step. In 2013, D. Venkatasekhar et al. [31] used the PSO method to reduce the search for the best domain block of each range block in the FIC method. The similarity between these blocks cannot be calculated unless they have the same type. The blocks in the domain and range sets are partitioned into three classes according to the coefficients of the third-level wavelet. For each range block, the similarity is measured only in the domain block from the same class. Only four transformations are required to determine the similarity in the dihedral transformation [30]. The steps of the modified fractal encoding according to the swarm method [32] is as follows:

Algorithm for the fractal image compression
Step1. Set the size of the swarm to be proportional to (M-$2r$+1) which represent the maximum number of iteration, the position and the particles is initialized randomly.
Step2. Finding MSE between the particles position (domain block) and range block as a fitness value.
Step3. If the fitness of the new best position is better, then the swarm best position is updated.
Step4. The algorithm is stopped if after some maximum iteration the best position is not changed.
Step5. Using (7) and (8) to update the particle best position, and go to step 2.

4.2 Harmony Search

The relationship between playing music and finding an optimal solution leads to the development (creation) of the HSA. Finding harmony in music is analogous to finding an optimal solution in an optimization method. After the introduction of the HSA music optimization algorithm by Geem et al. [17], its efficiency and effectiveness has been developed and improved by various researchers (for example, see [3, 18, 33]).

Obtaining the optimal harmony is the goal of HSA. Therefore, the following three potential methods should be implemented to satisfy this goal:

1. Playing for memory;
2. Pitch amendment;
3. Randomization.

In 2001, Geem et al. [17] recognized the resemblance between the music improvisation methods and finding the optimal solution to difficult problems. The researcher formalized three methods as part of the optimization algorithm developed. The following are the main steps of the HSA:

1. HM search;
2. Pitch amendment;
3. Randomization.

These parts are also considered the main parameters of the HSA [3, 34], which are described as follows:

1. Initialization: The program parameters are defined, and the HM is created with random solutions. All the solutions are evaluated by an evaluation or objective function.
2. Harmony improvisation: A new solution is formed. The three parts of the HSA are utilized to determine which value will be assigned to each variable in the solution.
3. Selection: The best solution (harmony) is chosen when the termination condition is achieved.

Classical Harmony Search Algorithm

Define objective function $f(x), x = (x_1, x_2, \dots, x_d)^T$
Define harmony memory consideration rate (r_{accept})
Define pitch adjustment rate r_{p_a}. Harmony in addition to other harmony parameters is generated randomly.
While ($t <$ max M) Do % M is the max number of iteration
    While ($i \leq N$) Do
    % N is the number of variables
        If ($rand < r_{p_a}$) certain amount is added to adjust the r_{p_a} value
        else
          Choose another random value
        end if
    end while
  Accept the new solution
end while
   Determine the best solution
end

The aforementioned algorithms with some parameters are reviewed as follows:

1. The maximum number of iterations is used as a terminator.
2. The size of the HM is used to determine the number of solutions to be saved in the HM.
3. The memory consideration rate represents the new solution from the memory solutions.
4. The pitch adjustment rate is used to add a specific rate to the modified rate of the memory.

The Proposed Algorithm
Step1. Initialize the harmony memory   a. A given image M is partitioned into non-overlapping blocks $R=\{R_1,R_2,\dots,R_m\}$ of size $r\times r$ called

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range blocks, where $m = (M/r)^2$, and overlapping blocks $D=\{D_1,D_2,\dots,D_n\}$ of size $2r\times 2r$ called domain blocks, where $n = (M-2r+1)^2$.

b. For each range block R_i, choose domain D_k, $k=1,\dots,n$ and a suitable contractive affine transformation w_{ik} that satisfied $d\big(R_i, w_{ik}(D_k)\big) = min\, d\big(R_i, w_{ij}(D_j)\big)$

where w_{ik} is a contractive affine transformation, $w_{ik} : D_j \to R_i$, d refers to the mean square error (MSE) between R_i and w_{ik} where $w_{ij} = \theta_{ij} * T_j$, T_j represented the contraction transformation $T_j : D_i \to R_i$, and can be described as follows:

D_j is divided into non-overlapping blocks of size 2×2, where the pixel value of the transformed block $T_j(D_j)$ is computed from the average of the four pixels in the block of D_j, the mapping θ_{ij} is performed in two steps;

- The block $T_j(D_j)$ is carrying out using eight isometries which was given in Figure 4.
- The pixel values of the output block from first step is transformed by W_{ij}, such that, $W_{ij}(z) = s_i z + o_i$, where the s_i and o_i as in equations (4) and (5).
- This comparison resulting $T_j = [x_i, y_i, f_j, s_j, o_j]$

Step2. The form of the harmony memory (HM) is as follows:

$$HM = \begin{pmatrix} T_1 \\ T_2 \\ \vdots \\ T_{HMS} \end{pmatrix} = \begin{pmatrix} x_1 & y_1 & f_1 & s_1 & o_1 \\ x_2 & y_2 & f_2 & s_2 & o_2 \\ \vdots & & \ddots & & \vdots \\ x_{HMS} & y_{HMS} & f_{HMS} & s_{HMS} & o_{HMS} \end{pmatrix}$$

where HMS should be between 50 and 100.

Recognize the worst member T_{worst}, such that $T_{worst} \in HMS$

Step 3. Suppose a random solution T_r, $T_r = [x_r\ y_r\ f_r\ o_r\ s_r]$

Step 4. Now, choosing any value from HM (random value) by HMCR (harmony memory consideration rate) where 0 < HMCR < 1. Let this random value be $T_i = [x_i\ y_i\ f_i\ s_i\ o_i]$, $T_i \in HM$.

Step 5. Let T' be a new harmony vector, $T' = \emptyset$

If $u(0,1) \le HMCR$ for all $i = 1,2,\dots,HMS$, where u is a uniform random number generator

Step 6. Choose a new solution $\{T_1', T_2', \dots, T_i^{HMS}\} \in HM$

Let $T_i' \in \{T_1', T_2', \dots, T_i^{HMS}\}$

If $u(0,1) \le PAR$, where PAR is adjusting, such that, $T_i' = V_{i,k}$, and $V_{i,k}$ is the pitch adjusting value.

Step 7. Now, evaluation the new harmony vector T_i' by comparing T_i' with the worst value $T_{worst} \in HM$, if $f(T_i') < f(T_{worst})$, where f is the fitness function, this comparison resulting a new harmony vector $T' \neq \emptyset, T' \in HM$, and then T_{worst} is excluded from HM i.e. $T_{worst} \notin$ HM.

5. IMPLEMENTATION AND ANALYSIS

The improved HSA is implemented using MATLAB, and the code is encoded in a PC with the specification Intel 2.5 GHz Core i7, with 8 MB memory. A sample of five gray scale images with a size of 512 × 512 is tested to show that, for the 4 × 4 range block size, a good compression ratio is obtained, but the computation time is increased. By contrast, for the 2 × 2 range block size, the compression ratio is decreased and the computation time is insignificantly improved. This inversely proportional relationship concludes that the 4 × 4 range block size is preferable for many applications because it satisfies the compromise between the computation time and the compression ratio. This result is depicted in Table 1.

The MSE is an evaluator used in measuring the average of the squares of the errors or deviations. The MSE strongly depends on the image intensity. In the case of image compression, this measure is used between original and compressed image values. The MSE is also considered one of the indications of image quality. The results of the experiments shown in Table 2 reveal that the range blocks with size 4 × 4 has better results than the range blocks with size 2 × 2, where the MSE is less and the peak signal-to-noise ratio (PSNR) is high. The PSNR is used to indicate the image quality, where its high value is mostly an indication of a high-quality compressed image. The ratio is defined via MSE and is inversely proportional to the MSE. Finally, the improved HSA is compared with the original FIC technique and the improved crowding method proposed in

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[15] to prove its efficiency. The comparison was in terms of encoding time, MSE, and compression ratio. Table 3 shows that the proposed method performed better in terms of these measures given the same samples of five images

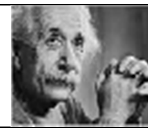
Table 1: Harmony Search Algorithm For Different Range Size In Terms Of Coding, Decoding Time And Compression Ratio

Images	Range	Initial Time	Coding Time	Decoding Time	Compression Ratio
	2×2	0.3758	0.0201	0.5936	3.6
	4×4	0.1101	0.0097	0.2591	8.5
	2×2	0.3752	0.0178	0.5288	2.7
	4×4	0.0985	0.0098	0.2564	5.5
	2×2	0.3237	0.0178	0.5621	4
	4×4	0.0978	0.0098	0.2595	7.1
	2×2	0.3289	0.0173	0.5622	2.7
	4×4	0.0981	0.0094	0.2584	6.7
	2×2	0.3260	0.0168	0.5618	3.8
	4×4	0.0978	0.0099	0.2635	8.7

Table 2: PSNR And MSE For Different Range Block Based On HAS

Images	Range	PSNR	MSE
	2×2	12.11	0.07
	4×4	14.50	0.03
	2×2	7.13	0.38
	4×4	12.04	0.06
	2×2	7.03	0.113
	4×4	10.53	0.08
	2×2	9.06	0.039
	4×4	15.8	0.02
	2×2	10.01	0.08
	4×4	15.14	0.03

Table 3: Comparison Between Jacquin Approach, Genetic And The Proposed Harmony For Range Block Of Size 4

	Images					
Fractal image compression based on Jacquin Approach	Coding Time	4.01	5.32	5.32	6.91	6.20
	MSE	0.81	0.89	0.94	0.91	0.83
	Compression Ratio	11.6	9.21	10.82	9.41	12.1
Fractal Image Compression based on Crowding method []	Coding Time	2.13	2.13	2.13	2.13	2.13
	MSE	0.026	0.026	0.026	0.026	0.026
	Compression Ratio	7.04	4.33	5.72	6.03	7.16
Fractal Image Compression based on Harmony Search Algorithm	Coding Time	0.11	0.108	0.107	0.107	0.107
	MSE	0.035	0.062	0.088	0.026	0.030
	Compression Ratio	8.5	5.5	7.1	6.7	8.7

6. CONCLUSION

The properties of the fractal function have been investigated over the years, and their inherent complexity, from the extreme sensitivity of the system to the initial conditions, was derived. These functions are used to model many real-life problems. Fractal image compression is one of the important applications. However, this approach has an optimization problem. Several optimization methods have been used, but the naturally inspired algorithm is preferred. The phenomena that mimic the musical process to search for the perfect state of harmony is used in this study to ensure a short coding time, a large storage area, and a high quality with less error ratio. In such methods, some degree of randomness should be added, which is an attempt to approximate the best solution and increase the efficiency. The combination between randomness and rules shows a promising result. The results of the experiments show that the image quality, coding time, and compression ratio are improved when using the proposed approach compared with the other optimization approaches. For more enhancements of this approach, we suggest utilizing of hybridizing between genetic algorithms and harmony search method to solve fractal inverse problem.

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