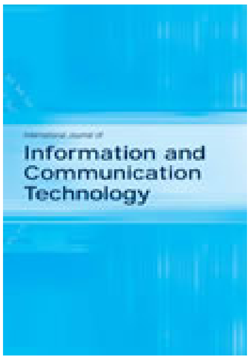

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An alternative method for generating fractal art patterns based on the balanced optimiser algorithm

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An alternative method for generating fractal art patterns based on the balanced optimiser algorithm

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Abstract: Fractal art patterns are widely used in fields such as artistic creation, data visualisation, and scientific simulation. The existing fractal pattern generation methods often face the problems of insufficient pattern diversity and low generation efficiency. This article proposes a fractal art pattern generation method based on the equilibrium optimiser (EO) algorithm. Firstly, using fractal iterative function system to define the solution space of key parameters; secondly, the balanced optimiser algorithm is introduced to perform global search and local optimisation of parameters; and finally, the complexity, symmetry, and diversity of the generated patterns were quantitatively evaluated through experiments. The results indicate that this method improves the generation efficiency while maintaining the complexity of fractal patterns, and significantly expands the diversity of patterns. This study not only enriches the technical means of fractal art creation, but also provides a new perspective for the application in art design.

Keywords: fractal art patterns; balanced optimiser algorithm; iterative function system; IFS; parameter optimisation.

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1 Introduction

The most fable newcomer in geometry is fractal geometry. Fractal curves have captivated many individuals since its origin, and several sectors including natural sciences, architecture, computer graphics, and musicology have been keen to include fractal theory into their respective study domains. Under the direction of colour and aesthetic guidelines, points, lines, and surfaces produce a good known as art design. Daykin et al. (2008) hold that art design follows a creative law of 'repetition and change'. 'If there is only repetition without change, the work will inevitably be monotonous and dry; if there is only change without repetition, it is easy to fall in a scattered and disorderly state'. Likewise, fractal algorithms' images exhibit strong degrees of 'repetition and change' properties. Integrating fractal theory into modern design research will transform all the techniques of art design, which will eventually influence the art creation itself, depending on the study basis of mathematical functions, computer algorithms, program design, and art design.

Fractal art pattern creation technology has lately been extensively used in computer graphics (Liu, 2022), data visualisation (Tian et al., 2019), and creative design domains (Chung and Ma, 2005). Nevertheless, conventional fractal pattern generating techniques mostly depend on hand design and parameter modification; their generating process is complicated and lacks automation. Particularly in the domains of art and design, designers have more expectations for the variety, complexity, and aesthetic effects of patterns, and current approaches are challenging to satisfy these demands concurrently. An important research challenge in this topic is how to maximise the fractal pattern generating process, increase generating efficiency, and broaden the expressiveness of patterns by means of intelligent algorithms.

Powerful global search capabilities and adaptable properties of intelligent optimisation algorithms – such as genetic algorithm (GA), particle swarm optimisation (PSO), and differential evolution (DE) – have shown exceptional performance in handling challenging optimisation challenges. Industries, economics, scientific research, and other disciplines have all benefited much from these algorithms. Still in the exploratory stage, nevertheless, is the application of fractal art pattern generating. Though they can somewhat increase the optimisation effectiveness of fractal parameters, conventional optimisation techniques have limited support for the complexity and variation of patterns and are prone to become caught in local optima. Researching more effective optimisation techniques to raise the quality of fractal art pattern development is thus quite important.

Inspired by dynamic equilibrium theory, EO is a newly developed intelligent optimiser (Faramarzi et al., 2020). EO dynamically changes the search strategy to reach both global and local search capabilities and effectively investigates the search space by replicating the development process of equilibrium states in nature. Strong competitiveness of this method has shown in mechanical design, path planning, and engineering optimisation. By means of its effective exploration mechanism, the balanced optimiser not only helps optimise the choice of fractal parameters but also improves the diversity and complexity of patterns, thereby meeting the needs of art design.

First presented by Mandelbrot (1975), a mathematician at Harvard University and researcher at the Physics Department of IBM Research Centre in the United States, the study on fractal theory started in the 1970s. This geometric theory has given people a fresh viewpoint and study approach for seeing and comprehending natural objects since it helps to explain their chaotic traits. A complement and extension of Euclidean classical geometry, fractal theory has enabled mathematical language to be used to describe the natural world. Fractals might be argued to be a useful tool for exposing the inherent structure of nature and to approach the actual face of nature more precisely than conventional Euclidean geometry. Being a novel scientific theory, fractal theory is changing people's perspective of natural objects, correcting their habitual way of thinking and examination of art, and has had a great influence on pattern creation and visual aesthetics.

After years of constant research and development, fractal theory has grown to be a significant multidisciplinary topic as a theoretical instrument for investigating the objective laws and inherent linkages of complicated natural events. Widely used in many disciplines, this viewpoint and approach highlights the presence of the material world and generates appropriate development. According to the development trend of recent years, notably in the sphere of art and design, adding fractal theory into disciplinary research will eventually help the discipline to flourish.

Theoretically, fractal geometry provides the means to create fractal patterns; its fundamental concept is to build intricate patterns by iteratively and recursively. The most often utilised fractal structures to create rich and varied geometric designs are Mandelbrot fractal and Julia set fractal (Zhou et al., 2016). Commonly utilised fractal generating technique iterative function system (IFS) creates fractal patterns with self-likeness properties by means of linear transformations (Chua et al., 2005). Research grounded on fractal geometry has progressively added randomness to improve the variety and creative expression of patterns in recent years (Losa et al., 2016).

Although conventional fractal generating techniques have great aesthetic value in theory, their parameter adjustment procedure depends on the designer's knowledge, so generating efficiency is limited and it becomes difficult to satisfy the needs of complicated artistic design. To thus increase generating efficiency and efficacy, researchers have started investigating techniques combining intelligent algorithms to automatically optimise fractal parameters (Li et al., 2020).

Because of their strong global search capability, intelligent optimisation algorithms are extensively applied to address challenging optimisation problems. By replicating natural evolution events, GAs maximise fractal parameters and produce more varied and complex patterns (He et al., 2022). Appropriate for fractal synthesis with reduced parameter dimensions, PSO method uses the cooperative search properties of particles to rapidly locate optimal solutions (Gad, 2022). Furthermore used in graphic design have been simulated annealing (SA) (Thirunavukkarasu et al., 2023) and DE methods (Storn and Price, 1997).

Thanks to their strong search performance, certain newly developed optimisation techniques including grey wolf optimiser (GWO) (Mirjalili et al., 2014) and firefly algorithm (Gad, 2022) have been applied to raise the quality of fractal pattern synthesis recently. These approaches still have difficulties, though, in balancing generation efficiency with complexity.

Based on balance mechanism, equilibrium optimiser (EO) is a new intelligent optimisation method. Its main ability is to simulate dynamic equilibrium states, with both global search and local fine optimisation capability, therefore modifying the distribution of solutions (Tang et al., 2021). In mechanical optimisation, path planning, and engineering design – among other domains – this method has shown outstanding performance (Wang et al., 2023).

In the domains of design and art, EO algorithm application is still in its early phase. The effective exploration mechanism of EO algorithm offers the means to overcome this challenge since the generation of fractal art patterns requires balancing complexity and efficiency (Elmanakhly et al., 2021). This paper presents the EO algorithm into fractal art pattern generating and enhances the variety and aesthetic expression of the produced patterns by optimising the fractal parameters.

This work intends to present a fractal art pattern generating method based on the balanced optimiser algorithm, which integrates fractal geometry theory with intelligent optimisation algorithms to attain automation and diversification of the creation process. This article mostly makes three contributions: specifically, these three points are:

1 Constructed based on the IFS in fractal geometry, a fractal art pattern generating model is built, important parameters and their corresponding solution space are determined, and a fundamental framework for algorithm optimisation is developed.

2 Design an optimisation approach that fits fractal generating models, apply EO algorithm to globally search and locally optimise model parameters, and enhance the quality and diversity of produced patterns.

3 Comprehensively compare the performance variations between the balanced optimiser algorithm and conventional optimisation algorithms in fractal pattern generation.

2 Relevant technologies

2.1 Fractal theory

Mathematically speaking, fractals still lack a consistent definition and Mandelbrot himself has not offered a thorough theoretical one. Although his knowledge of fractals is still increasing, the always divided idea of fractals is continuously enhancing this theory. We may investigate some special characteristics of fractals since we are more interested about their application and development.

A set is said to be fractal if its operational or descriptive definitions match each other:

1 Any ratio has minute elements. Zooming in or out of fractal images will not lose features, so the nested structure of layers will always show and more levels can be split.

2 Both locally and internationally are somewhat erratic; conventional geometric terminology cannot adequately explain them. Fractals cannot be measured with the conventional scales like area and volume. Simple repetition rules allow one to understand the self-resemblance between the total and the parts even if their form is somewhat complicated.

3 Having a shape like this, one may use statistics or approximations. Usually, fractal images feature multi-level self-similar patterns.

4 The dimension exceeds that of topological dimension. In fractal theory, dimension is a crucial metric that shapes people's perspective of environment. People thus come to see that dimensions are not only integers but also fractions or even irrational quantities.

5 Most of the time, fractals may be produced iteratively and are characterised by quite basic techniques. Research of complicated forms depends much on IFSs.

2.2 Topological dimension and fractal dimension

Euclidean classical geometry and Cartesian coordinate system theory define the dimension in geometric space as the count of coordinates defining a point's position.

The relationship between points, lines, and surfaces can be represented by a mathematical expression, and this expression is related to the dimensionality. For example, an arbitrary point $M(x, y)$ on a plane can be represented in the following form:

$$M:\begin{cases} x = c_1 \\ y = c_2 \end{cases} \tag{1}$$

where c_1 and c_2 are the coordinates of point M, which are constants, so their geometric dimension is zero.

Any line segment (straight or curved) on a plane can be represented in the following form:

$$y = f(x) \tag{2}$$

The points (x, y) that satisfy the function f form a line segment in the plane. y can be represented by a function variable x with a geometric dimension of one. A line has only one dimension of length and is one-dimensional.

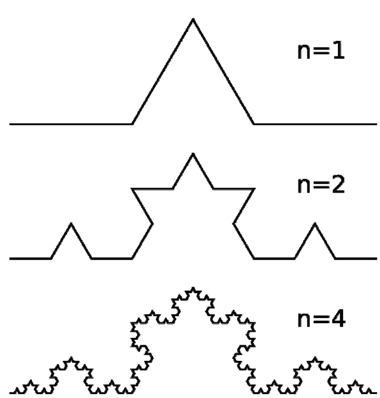
Any surface (plane or curve) in space can be represented in the following form:

$$z = f(x, y) \tag{3}$$

The points (x, y, z) that satisfy the function f form a surface in the plane. z can be represented by two functional variables x and y, with a geometric dimension of two. A surface is two-dimensional, and the space composed of surfaces is three-dimensional, with dimensions of length, width, and height. That is, points are zero dimensional, lines are one-dimensional, and surfaces are two-dimensional. The dimensions defined in this way are called topological dimensions.

All points, lines, and surfaces can be represented by $f(x)$, $f(x, y)$, and $f(x, y, z)$, and geometric objects with integer dimensions are regular and smooth geometries that can be measured using an integer dimensional ruler.

Figure 1 The generation of Koch curve



Step 2, at this time $n = 2$, repeat the process of the previous step for E_1 composed of four folded line segments to obtain E_2, a line segment composed of 16 polylines. Continuing to repeat the process of dividing each line segment into three equal parts and removing the middle line segment can be understood as a recursive process from E_n to E_{n+1}. The

Koch curve is obtained when n approaches infinity. The first few steps of the Koch curve generation process can be illustrated in Figure 1.

Fractal geometry reaches the description of 'irregular' geometric objects by extending the dimensionality from integers to fractions. Different fractal events demand different fractal dimensions to explain: the Koch curve with a dimension of 1.26, the shoreline with a dimension of 1.05–1.25, and the mountain and ocean surfaces with dimensions larger than 2. The fractal dimension value shows the complexity of the fractal set; hence, the more space the fractal set may fill.

2.3 Cantor triple diversity

Constructed recursively from the interval [0, 1], Cantor triplets follow these steps:

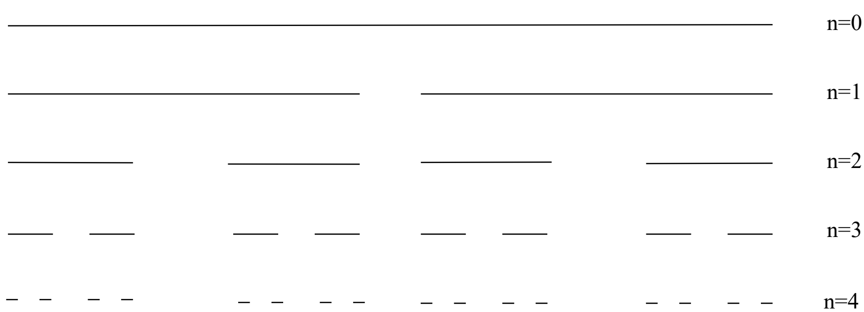
1 starting from the closed interval [0, 1]

2 divide the interval into three equal parts, remove the middle third of each interval again; repeat the process endlessly

3 remove the middle third of each interval once more.

Cantor triplet is the outcome, a set with an unbounded number of points.

Figure 2 Cantor triple diversity



Typical examples of fractals include Cantor triplets, in which every component has a form reminiscent of the whole. Expand any section while maintaining the general integrity of the construction. Each stage of the construction removes finite length intervals, while the remaining collection of points is still infinite. Cantor triplets have a total length that usually 0, hence the conventional 'length' of the set does not exist but the set contains an endless number of points. Cantor's triplet has infinite points, but it is uncountable, hence the number of points in its set is equipotential to the set of real numbers even though. Once perplexed mathematicians in the 19th century, the paradoxical character of its design now baffles them. From the standpoint of geometric relationships, however, the distribution of produced points is locally similar – that is, even locally similar between every stage of the process – called self-similarity.

2.4 Sierpinski gasket

It is a two-dimensional fractal structure widely used in the research of mathematics, computer graphics, and fractal geometry.

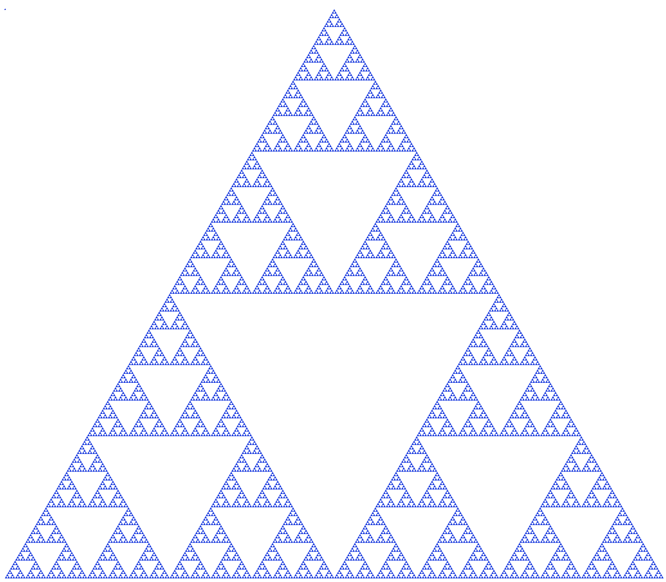
Constructed recursively from an equilateral triangle, Sierpinski shims follow these guidelines:

1 The initial state starts from a large equilateral triangle as the basis of the fractal.

2 Recursive rule, divide the current triangle into four small equilateral triangles, with each side measuring 1/2 of its original length. Remove the small triangle at the centre (forming an inverted triangular void). Apply the same rule recursively to the remaining three small triangles.

3 Infinite iteration, the remaining triangles get smaller as the number of recursion rises and finally create an infinitely fine Sierpinski shim with a self like structure. Figure 3 exhibits a Sierpinski triangle.

Figure 3 Sierpinski triangle (see online version for colours)



2.5 Sierpinski gasket

Inspired by the equilibrium in physics, EO is a fresh metaheuristic optimisation method. It simulating the process of particles reaching equilibrium in a physical system helps it to realise optimal aims. This method with great convergence speed and solution quality combines local development with global search.

Many elements affect the process of particle systems achieving equilibrium in physics: interactions between particles, internal random fluctuations, and external environmental variables of the system. EO models the process of solving optimisation challenges by using these properties. Starting from the first non-equilibrium state, the system gradually moves towards equilibrium state by means of particle contact; fine tune close to the equilibrium state to identify the best solution.

EO abstracts the 'equilibrium state' of the system, therefore capturing the ideal solution of the problem. The method dynamically changes the search methodology to progressively approach this equilibrium condition of the population.

Each generation (iteration), the equilibrium solution is computed by weighting the outstanding solutions of the current population:

$$x_{eq} = \sum_{k=1}^{K} \omega_k \cdot x_k \tag{4}$$

where x_k is the k^{th} excellent solution in the population, ω_k is the weight factor, which is inversely proportional to the fitness of x_k, and K is the number of excellent solutions.

EO reaches adaptive switching between global search and local development by varying the balancing factor. Changing formulas and parameter values is really easy and low processing complexity. The lower complexity has strong adaptability and robustness to various optimisation problems. The equilibrium solution helps the population stay out from local optima. Fit for discrete, continuous, and multi-objective optimisation problems. Therefore, EO model is easy to be combined with various optimisation techniques, such as anti-learning, anarchy and so on.

3 A fractal art pattern generation method based on balanced optimiser algorithm

Combining intelligent optimisation technology with fractal geometry theory, the fractal art pattern generating approach based on the EO algorithm suggested in this article achieves efficient and varied fractal pattern generating by optimising important parameters of the IFS. Combining lens imaging learning approach with tent chaos strategy to improve global search capability and local development capability, so obtaining better quality fractal pattern generating.

3.1 Construction of fractal generation model

The foundation of fractal geometry is the IFS, whose core lies in defining a set of affine transformations that can generate self-similar patterns. The IFS model is described in the following mathematical form: 1 Introduction of dynamic convolution.

$$w_i(x, y) = \begin{bmatrix} a_i & b_i \\ c_i & d_i \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} + \begin{bmatrix} e_i \\ f_i \end{bmatrix}, i = 1, 2, ..., N \tag{5}$$

where a_i, b_i, c_i, d_i, e_i, f_i is the parameter of the transformation, and N is the number of transformations. By continuously iterating these transformations, fractal patterns with complex geometric properties can be generated.

In this study, the Mandelbrot set, Julia set, or other specific fractal structures were first selected as initial templates. Then, the key parameters of IFS are defined as optimisation objectives, which control the shape, complexity, and symmetry of the fractal pattern.

3.2 Design and adaptation of balanced optimiser algorithm

Driven by dynamic balancing theory, the balanced optimiser algorithm is a global optimisation method. The central concept is to balance global exploration and local development by progressively approaching the ideal solution by modifying the distribution trend of the solution.

3.2.1 Tent chaotic mapping sequence.

By modelling the principle of equilibrium and hence approximating the global optimal solution, EO dynamically moves between solution exploration and development. EO's fundamental procedure consists in:

1 randomly producing starting solutions

2 dynamically updating the balance pool, guide the population to progress towards the optimal direction

3 balancing global exploration and local development using parameter perturbation and balance control.

The EO algorithm starts with a randomly generated population, where each individual represents a possible solution to the IFS parameter. The initial solution space is defined as:

$$P = \{(a_i, b_i, c_i, d_i, e_i, f_i) \mid a_i, b_i, ..., f_i \in [L, U]\} \tag{6}$$

where L and U are the upper and lower limits of the parameter, respectively.

The EO algorithm achieves population evolution through the following update rules:

$$x_i^{t+1} = x_i^t + r_1 \left(x_{eq}^t - x_i^t \right) + r_2 \left(x_{eq}^t - x_i^t \right) \cdot F \tag{7}$$

where x_i^t is the parameter value of the i^{th} solution in the t^{th} iteration, x_{eq}^t is the parameter value of the equilibrium state, r_1, r_2 is the random factor, and F is the control factor, dynamically adjusting the search intensity.

Through the introduction of chaotic variables, the Tent chaos technique enhances population initialisation and search variety. Early stage chaos mapping accelerates the convergence speed of the algorithm by means of unpredictability, ergodicity, and orderliness, therefore enhancing the population variety. Thus, this paper enhances the EO algorithm using the sequence initiation population produced by tent chaos, stated as follows:

$$Y_i^d = \begin{cases} 2Y_i^d, 0 \le Y_i^d \le 0.5 \\ 2\left(1 - Y_i^d\right), 0.5 \le Y_i^d \le 1 \end{cases} \tag{8}$$

where d is the variable dimension and i matches the particle count. As the process of creating Tent mapping sequences inside the reasonable domain generates small periods {0.2, 0.4, 0.6, 0.8} and unstable fixed points {0, 0.25, 0.5, 0.75}. Random variables are incorporated in the above formula to disturb the sequence and help one avoid becoming caught in small and unstable periodic points during iteration. The Tent mapping sequence guarantees additionally the randomisation, traversal, and orderliness within a controllable random range.

The Tent chaos approach is applied at the population's beginning stage to produce parameters guaranteeing its diversity. Little chaotic perturbations are added to individual parameters throughout the iteration process to increase global search capacity and prevent local optimal traps.

3.2.2 Lens imaging anti learning strategy

We propose a reverse learning technique based on lens imaging principle to increase the capacity of EO algorithm to break out from local optima. Inspired by the reverse concept of optical lens imaging, lens imaging reverse learning method is an enhancement technique in optimisation algorithms, mostly used to improve global search ability, help algorithms get rid of local optima, and enable exploration ability of solutions, so enabling optimisation algorithms. This approach guides the search process to extend in a more all-encompassing direction by imitating the 'mirror reflection' or 'optical path reversal' behaviour of the answer, therefore producing new candidate solutions. By means of mirror reflection or reverse mapping, the lens imaging anti-learning technique investigates possible ideal areas outside the present search range.

Solution update in conventional lens imaging learning methods is based on the light travelling through the lens approaching the focus point. On the other hand, the anti-learning approach simulates the reverse path of light or the process of creating virtual images, therefore boosting the diversity and unpredictability of exploration. Under the following presumption: always exists a corresponding inverse solution X^*. Find the possible solution X in the solution space. Inverse solution X is revised to the optimal solution if its fitness value is higher than that of the feasible solution.

The lens imaging learning approach is applied to improve the local development capacity of solutions by simulating the imaging principle of optical lenses. The revised equation is:

$$x_i^{t+1} = x_i^t + \alpha\left(x_f - x_i^t\right) + \beta\left(x_f - x_b\right) \tag{9}$$

where α, β is the dynamic learning factor; x_f is the virtual focus, computed depending on the position of the optimal and suboptimal solutions; x_b is the current worst solution utilised to improve directionality. While lowering the likelihood of the algorithm stagnating in unsatisfactory solutions, the lens imaging method speeds the local convergence of the solution.

3.2.3 Specific steps of improved EO algorithm (TLEO)

The specific steps of the improved EO algorithm are as follows:

1 Initialise the IFS model and parameter range, use the EO algorithm to initialise the population, and set the input parameters for algorithm initialisation.

2 Introduce the sequence generated by Tent chaos to initialise N particle populations, iteratively update the populations, and optimise IFS parameters.

3 Generate fractal patterns and calculate the fitness values of each individual particle, record and screen out the 8 best balanced candidate particles so far.

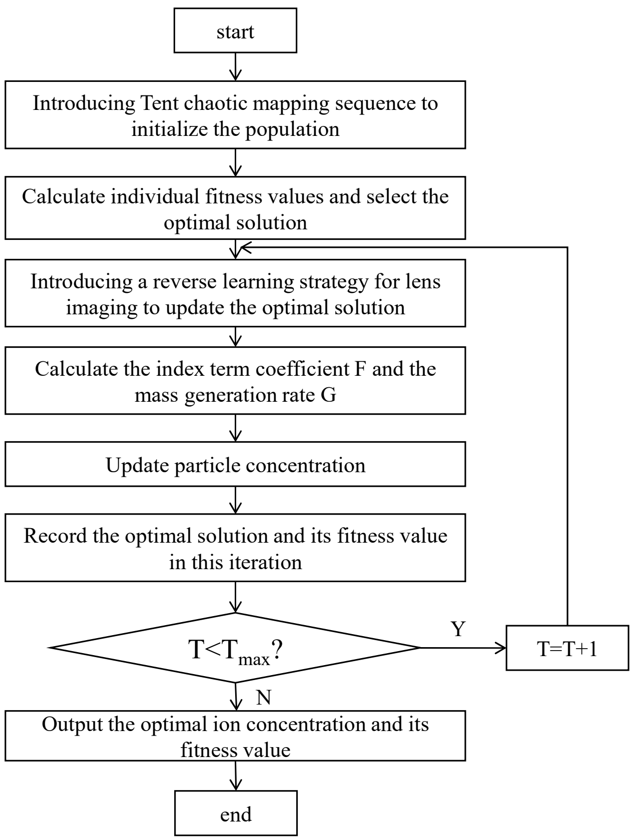
4 Build a balanced state pool and select candidates.

5 Introducing a lens imaging reverse learning strategy to update the optimal solution: Introduce a lens imaging reverse learning strategy to X, obtain the reverse solution X^*, and if the fitness value is $f(X_i) < f(X_i^*)$, add reverse solution X_i^* instead of X_i to the particle population and record the optimal particle concentration.

6 Repeat the iteration until the termination condition is met.

7 Output optimal parameters to generate the final pattern.

Figure 4 TLIL-EO algorithm process



4 Experiment

4.1 Experimental setup

Mostly using hardware devices like Intel (R) Core (TM) i7-12700H, four RTX, 2080/RTX 2080 Ti, etc., this paper depends on Technical models implemented in this paper use PyTorch, Python 3.9, NumPy, Matplotlib, etc. Initialisation uses tent chaotic mapping. The acceleration factor in the PSO technique is 1.5 while the inertia weight is 0.7.

The testing environment runs Microsoft 64 bit operating system and employs MATLAB code for all algorithm performance tests; Set the population size to 100; the maximum number of iterations to 1,000; then, run the process 50 times.

This work selected a total of 12 single peak and multi-peak benchmark functions for algorithm optimisation testing in order to validate the performance of the proposed TLEO algorithm. For function testing the TLEO method was compared with conventional EO algorithm (Elmanakhly et al., 2021), PSO algorithm, and moth flame optimisation (MFO) algorithm.

4.2 Experimental results and analysis

Figure 5 exhibits the test findings. The TLEO method beats most other methods in terms of computing performance for the great majority of unimodal and multimodal test functions. The TLEO algorithm has greatly enhanced convergence accuracy and stability over the EO method, so confirming its benefits in global exploration and the capacity to avoid local optima. Early on in the iteration, the TLEO method converges noticeably faster than other methods; it also has more accuracy in the middle and later phases of convergence This is a result of the Tent chaotic mapping sequence introduced to start the population, hence enhancing population diversity and speeding optimisation efficiency. By means of high convergence precision, the lens imaging anti-learning method improves the capacity to leap out of local optima and carry on global exploration in the middle and later stages.

Figure 5 Test function convergence curve (see online version for colours)

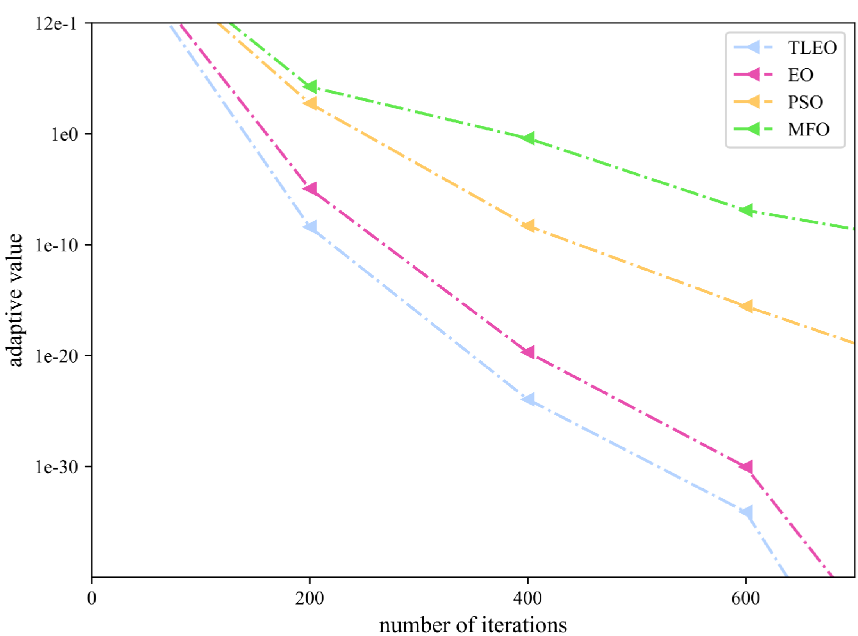


Figure 6 Comparative experimental results (see online version for colours)

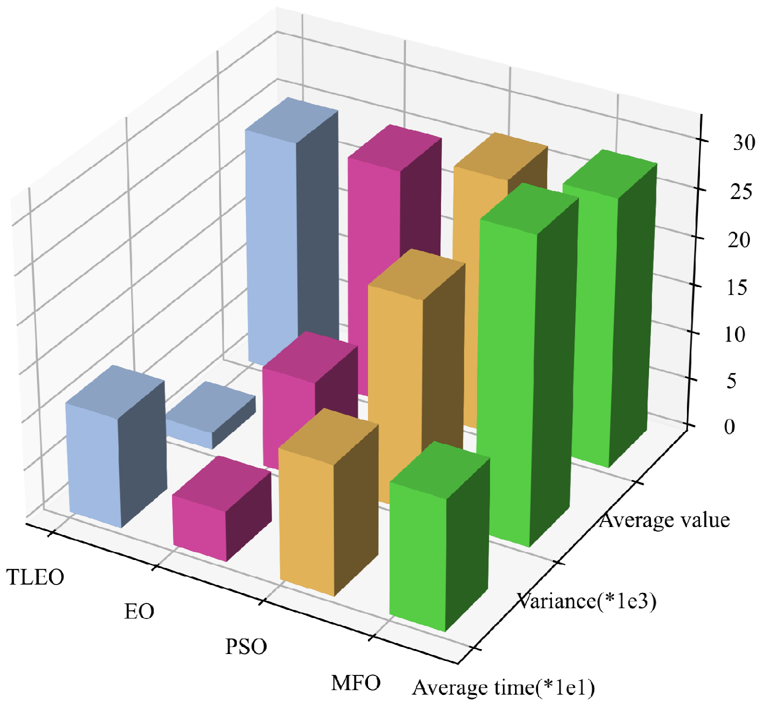


Figure 7 The generated fractal pattern (see online version for colours)

As shown in Figure 6, the optimisation efficiency of the TLEO method was matched with other enhanced algorithms based on the EO algorithm to validate its performance even more. Referring to the global minimum value of the test function, a fixed optimisation value was specified, and the stopping condition throughout every algorithm iteration was less than the fixed optimisation value or reaching the maximum iteration number. Three performance indicators – optimisation mean, variance, and average time – evaluated each algorithm's performance under the identical testing environment and parameter values. By means of comparison, it was discovered that the enhanced EO algorithm offers more benefits than other such algorithms. In terms of optimisation capacity and efficiency, the TLEO algorithm beats the MFO method both in terms of single and multi-peak test functions.

Figure 7 shows the generated fractal pattern.

5 Conclusions

Based on the EO algorithm, this work suggests a fractal art pattern generating technique and confirms its efficiency by means of tests. Especially in terms of pattern symmetry, detail complexity, uniformity of pixel density distribution, and convergence efficiency, EO shows advantages over conventional optimisation techniques including GA and PSO. The EO method may dynamically balance global exploration and local development during the search process by including a dynamic balancing factor, therefore preventing the issue of local optimal solutions. Furthermore included in this paper are tent chaotic mapping and lens imaging anti-learning techniques, which greatly enhance the diversity, exploratory character, and convergence efficiency of the optimisation process and produce high degrees of visual effects and structural complexity of the produced fractal art patterns. In several respects, the experimental results reveal that the EO method beats GA and PSO. In particular, EO produces not only more exact and symmetric fractal patterns but also converges to high-quality solutions in a shorter time and produces very great stability and durability. Consequently, the EO method finds general use in image processing, fractal art pattern synthesis, and other domains. One can investigate future directions in line with the following elements. This article mostly uses the EO algorithm for single objective optimisation problems; in the future, it can be extended to multi-objective optimisation problems, such producing several or unique fractal patterns. The EO algorithm is intended to perform well in multi-objective situations by use of suitable fitness functions and non-dominant sorting techniques. The EO method has shown good performance; yet, on some challenging issues the convergence speed and computing efficiency of the algorithm still require development. Future developments in adaptive mechanisms, hierarchical search strategies, or hybrid optimisation techniques could help to raise local exploration accuracy of the algorithm and global search capabilities. Combining EO algorithm with other metaheuristic algorithms (such as GA, ant colony algorithm, artificial fish swarm algorithm, etc.) can be tried to form a hybrid optimisation algorithm, so using the advantages of various algorithms and improving its performance in diverse fractal image generating activities.

Declarations

All authors declare that they have no conflicts of interest.

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