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Decorative Fractal Pattern Generation Method Based on Improved Quantum Genetic Algorithm

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Abstract. *Traditional decorative pattern design often relies on the imagination of the designer, but these limited resources may limit the variety and innovation of designs. Manually designing and experimenting with various patterns can be time and resource intensive, especially when complex geometric structures and textures are involved. Therefore, this work proposes a decorative fractal pattern generation method based on an improved quantum genetic algorithm, which can help to solve the problems of creativity, time, cost, diversity and personalisation needs in decorative pattern design. Firstly, the basics of fractal theory are analysed, including the definition and characteristics of fractal patterns, and a variety of traditional fractal pattern generation methods under mathematical logic thinking are investigated. Then, an improved quantum genetic algorithm is proposed in order to further improve the convergence speed of quantum search and increase the diversity of the population. A new quantum rotating gate adjustment rule was designed in order to process the quantum rotation angle in real time. In addition, a catastrophe operator based on a tournament selection mechanism is employed in order to overcome the phenomenon of prematurity. Finally, a unique fitness function was designed considering three aspects of fractals, such as aesthetics, symmetry, and decorative effect. Experimental simulation results show that the improved quantum genetic algorithm can obtain better solutions than other quantum evolutionary algorithms. The example results of wall decoration patterns verify the feasibility of the proposed method.*
Keywords: Genetic algorithm; Quantum computing; Fractal theory; Decorative patterns; Catastrophe operator

1. **Introduction.** Fractal patterns exhibit unique and beautiful geometric forms and self-similarity, giving a sense of symmetry, order, and the beauty of complexity [1, 2]. The study of fractal patterns allows for an in-depth exploration of aesthetic principles and laws in nature and art. Fractal patterns are widely found in nature and man-made objects. By studying fractal patterns, we can reveal the laws and patterns in nature and help us better understand and recognise complex structures and forms, such as the bifurcated structure of leaves and the shape of clouds [3, 4]. Fractal geometry, as a representation of nonlinear dynamical systems, can help study and analyse the behaviour of nonlinear dynamical systems. The ability of fractal patterns to capture the scale invariance and complex structure of attractors in dynamical systems provides a tool to study complex systems [5, 6]. Fractal patterns can be applied in many fields, for example, fractal patterns can be used in artworks, decorations, wall decorations, fabric designs, etc [7] to create unique visual effects and aesthetics in art and design.

Fractal patterns have a wide range of applications in architectural interior design. Wall and ceiling decorations using fractal patterns can add a unique artistic atmosphere to interior spaces. The geometry and self-similarity of fractal patterns can give walls and ceilings richer textures and details, creating a sense of visual richness and dynamism [8, 9]. Fractal patterns can be used to design patterns for floor tiles, carpets or flooring to create interesting geometric textures and a sense of artistry. The detail and regularity of fractal patterns can add comfort and visual enjoyment in floor decoration. Fractal patterns can be used in furniture and decorative items such as sofas, curtains, and lamps. The fractal pattern design of these furniture and decorative items can provide a unique visual focal point for the interior environment, adding artistic ambience and individuality. Decorative partitions using fractal patterns can subtly partition interior spaces, providing privacy while keeping the space open and fluid. The form and regularity of fractal patterns can create subtle dividing lines and transitional effects [10, 11, 12].

By applying fractal pattern design, architectural interiors are able to create unique visual effects, rich textures and artistry, bringing a higher level of aesthetics and personalisation to interior spaces. It can complement other design elements to shape a unique spatial atmosphere and user experience. Therefore, this study aims to achieve innovative and diverse generation of decorative fractal patterns through quantum genetic algorithm. By introducing quantum computing ideas into the evolution of the genetic algorithm, it can help generate richer, unique and innovative fractal pattern designs. In addition, by improving the quantum rules, the speed and quality of fractal pattern generation can be improved and the consumption of computational resources can be reduced.

1.1. **Related Work.** research in the field of fractal pattern generation has focused on the following areas:

Firstly, for the optimisation and improvement of fractal algorithms, researchers have devoted themselves to improving the generation efficiency and quality and exploring faster and more accurate generation methods. Aguirre et al. [13] implemented an optimisation technique based on fractal nature by modifying the chaotic optimisation algorithm. The method first implements the fractal property in weighted gradient direction chaotic optimisation and compares it with conventional optimisation algorithms. Fronczak and Fronczak [14] presented fractal graph optimisation algorithms for three types of graph optimisation problems (all-pairs shortest path, all-pairs maximum flow and search). Each algorithm utilises a hierarchical decomposition approach to solve a specific type of optimisation problem. Tavazoei and Haeri [15] proposed a continuous optimisation problem solving method that can be applied in fractal pattern generation to achieve better optimisation results. They search the state space of a continuous optimisation problem iteratively to find a globally optimal solution.

Secondly, researchers have focused on the personalisation and controllability of fractal pattern design by introducing user needs and preferences for customised pattern generation. In addition, there are studies focusing on the application of fractal patterns in various fields, such as architectural design, interior decoration, and digital media. Meanwhile, by combining fractal patterns with other techniques, such as machine learning and genetic algorithms, researchers aim to generate more innovative and diverse patterns. Pang and Hui [16] proposed a method for personalised fractal pattern generation using interactive genetic algorithm. By interacting with the user, the user's needs and preferences are used as the objective function of the genetic algorithm, so that the generated fractal patterns are more in line with the user's personalised requirements. By introducing the interactive genetic algorithm, the researchers successfully achieved personalised fractal pattern generation, which enables the user to participate in the generation process and satisfies the user's personalised needs and curiosity. Abboushi et al. [17] proposed a method for fractal image aesthetic design based on user preferences. By collecting user evaluations of different sample images, a prediction model is built to determine the user's aesthetic preferences and generate a personalised fractal image design that meets the user's needs. Chao [18] proposed a user-driven interactive fractal image generation method using a genetic algorithm. By combining genetic algorithms and user feedback, user evaluation and preferences are used as optimisation functions to provide users with a customised fractal image generation experience. User participation and feedback help to generate image results that are more in line with user needs and preferences.

1.2. Motivation and contribution.

Fractal pattern generation usually involves complex geometric structures and textures that require highly accurate optimisation and tuning. Traditional genetic algorithms may encounter inefficiencies when dealing with complex optimisation problems [18, 19], especially when confronted with high-dimensional spaces and large-scale search spaces. Quantum genetic algorithms have a greater ability to handle and optimise complex problems, and through techniques such as quantum gate operations in quantum computing [20, 21], the generation and optimisation of fractal patterns can be performed more accurately. Therefore, the application of quantum genetic algorithms to the problem of decorative fractal pattern generation is proposed. The main innovations and contributions of this work include:

(1) New quantum rotating-gate tuning rules were devised in order to process quantum rotating angles in real time, thus improving the convergence speed of the quantum search and increasing the diversity of the population, and then a catastrophe operator based on a tournament selection mechanism [22, 23] was employed in order to overcome the phenomenon of prematurity.

(2) A decorative fractal pattern generation method based on improved quantum genetic algorithm is proposed, and specific implementation steps are given. A unique fitness function is designed considering three aspects of fractal aesthetics, symmetry, and decorative effect. The scores are weighted and summed according to specific needs. These specific needs can be adjusted at any time according to the different demand tendencies of the customers.

2. Basic knowledge of fractal theory.

2.1. Definition of fractal patterns.

The introduction of the concept of fractals and the establishment of the theory can be traced back to the 1970s. Fractal theory originated from the mathematician Mandelbrot's study of the phenomenon of self-similarity. He observed that many forms and structures in nature exhibit self-similarity, i.e., similar shapes can be seen no matter how many times they are magnified. Mandelbrot called this self-similarity feature a fractal.

The establishment of fractal theory relies heavily on advances in computer technology. Through computer simulations and graphical representations, people are able to better understand and study fractal structures. Fractal theory is not only applied in the field of mathematics, but also penetrates into various fields such as physics, biology, and economics. The core idea of fractal theory is to generate complex forms through simple rules and repetitive processes. It emphasises the disorder and randomness in nature and presents an aesthetic sense of rules and order. The formulation of the concept of fractals and the establishment of the theory have played an important role in recognising and explaining complex phenomena in nature, and have had a far-reaching impact on people's understanding of the structure and laws of nature. A fractal can be defined as a geometric shape or mathematical structure with self-similarity and infinite detail. It is a pattern that can be repeated at any scale, and similar shapes can be seen no matter how large the scale at which it is viewed, i.e., it has the same statistical properties.

2.2. **Characteristics of Fractal Patterns.** Fractal theory has a wide range of applications and can be used to describe many phenomena and structures in nature, such as the shapes of clouds, the contours of mountain ranges, the branches of plants, and the waveforms of an electrocardiogram. Through the introduction of the concept of fractals, people are able to better understand and explain complex natural phenomena and have found many interesting applications in science, art and engineering. Fractal patterns have several characteristics:

(1) Self-similarity: The self-similarity of a fractal pattern is its most remarkable feature. Similar shapes and structures can be found no matter how large the scale of observation. Even if a part of the pattern is enlarged or reduced, the same pattern as the whole can still be seen. This self-similarity can be either strict, i.e., exactly the same at every zoom level, or statistical, i.e., statistically similar.

(2) Infinite detail: Fractal patterns produce infinite detail as they are continuously subdivided. Zooming in on the fractal pattern multiple times reveals more and more fine structure and detail. This infinite detail makes the fractal pattern rich in information and texture at all scales.

(3) Scale invariance: Fractal patterns maintain similar statistical properties at different scales. The statistical properties of fractal patterns (e.g., dimensionality, fractal parameters, etc.) remain constant even when viewed at different scaling levels. This scale invariance makes fractal patterns have a wide range of applications in mathematics and scientific research.

(4) Complexity: Fractal patterns characterise many complex systems in nature. They are often generated by simple rules and repetitive processes, yet exhibit complex forms and structures. The complexity of fractal patterns reflects the richness of information and chaos.

3. Methods for generating fractal patterns in mathematical logic.

3.1. **Iterated Function System.** Iterated Function System (IFS) is a method for generating fractal patterns based on successive transformations [24, 25]. By defining a set of transformation functions and weighting coefficients and applying these functions continuously and iteratively, a fractal pattern is finally obtained. Koch snowflake and the Sierpinski triangle are generated by the IFS, as shown in Figure 1 and Figure 2, respectively. It is obvious that they both have the self-similarity property.

The basic method of IFS generation is as follows.

$$X' = f(X) \tag{1}$$

where X is a point in space and f is a system of functions consisting of several affine transformations (scaling, rotation, translation). Each affine transformation can be expressed as:

$$f(x, y) = \big(ax + by + e, cx + dy + f\big) \tag{2}$$

where a, b, c, and d control scaling and rotation; e and f control translation.

For an IFS containing N affine transformations, it can be expressed as follows.

$$F(X) = \{f_1(X), f_2(X), \dots, f_N(X)\} \tag{3}$$

At each iteration, a random transformation f_i is chosen from F and applied to the current point X to obtain a new point X'.

$$X' = f_i(X) \tag{4}$$

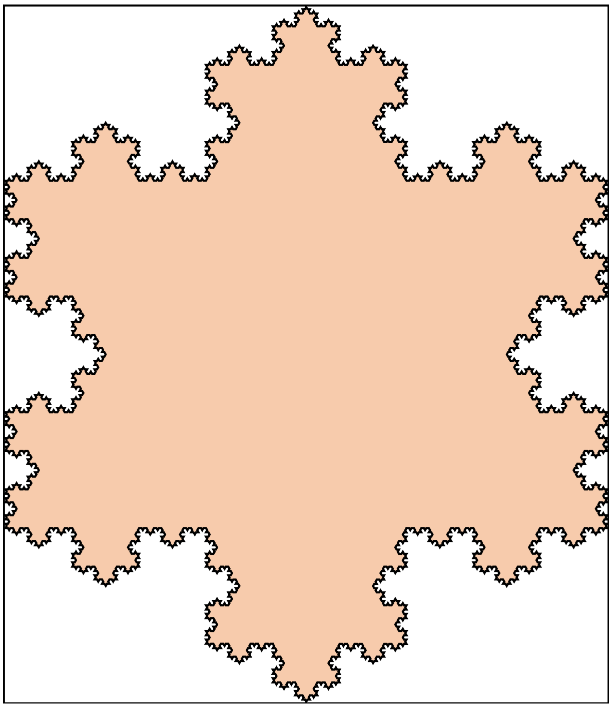

Figure 1. Koch snowflake

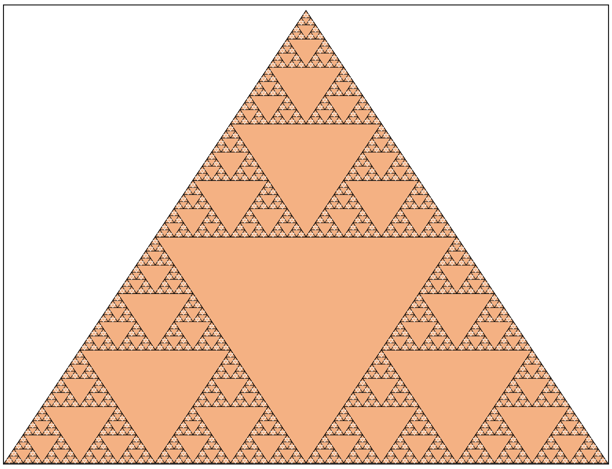

Figure 2. Sierpinski triangle

During the iteration, starting from some initial point X_0, the transformation is repeatedly selected and applied.

$$\begin{cases} X_1 = f_1(X_0) \\ X_2 = f_2(X_1) \\ X_3 = f_3(X_2) \\ \dots \end{cases} \tag{5}$$

After a sufficient number of iterations, the resulting point set will asymptotically approach the desired fractal pattern.

3.2. **Fractal Noise.** Fractal Noise is a method of generating fractal patterns based on randomness. It can be used to create textures and patterns with fractal characteristics by iterating, merging and amplifying the noise signal several times. Fractal noise is often used to generate realistic textures, terrain, and clouds, among other effects. Common

Fractal Noise algorithms include the Midpoint Displacement Method, Rock Fractal, and the Vladivsky Method. The key to generating Fractal Noise patterns is usually fractional brown circle noise, as shown below:

$$fBm(x, y) = \sum \left(\frac{noise(freq_x * x, freq_y * y)}{freq^{(H+n)}} \right) \tag{6}$$

where $freq_x$ and $freq_y$ are frequencies in the x and y directions; $freq = \max(|freq_x|, |freq_y|)$; H is the roughness parameter, which controls the fractal dimension; N is the number of octaves, which controls the level of detail.

3.3. **Linear recursive methods.** The linear recursive method is a fractal generation method based on a system of linear equations. By defining a set of linear equations and initial conditions, the system of equations is solved step by step iteratively to obtain a fractal pattern. A classical linear recursive fractal is the Sierpinski carpet. For the linear recursive method of generating fractal patterns the computational formula can be described by the following recursive equation:

$$\begin{cases} x_{n+1} = a \cdot x_n + b \cdot y_n + e \\ y_{n+1} = c \cdot x_n + d \cdot y_n + f \end{cases} \tag{7}$$

where (x_n, y_n) is the coordinate of the nth point; (a, b, c, d, e, f) is the parameter of the linear transformation matrix. By continuously iterating the above equations, a graph with fractal features can be generated.

3.4. **Stochastic fractal generation methods.** Random fractal generation method is a fractal pattern generation method based on randomness. By randomly selecting and transforming different parts of the image, and then repeating and combining them, the fractal pattern is finally generated. This method is often used to generate artistic abstract fractal patterns.

A simple random fractal generation method can use the following random translation transform function:

$$\begin{cases} x_{n+1} = a \cdot x_n + b \cdot r_1 + e \\ y_{n+1} = c \cdot y_n + d \cdot r_2 + f \end{cases} \tag{8}$$

where (r_1, r_2) is a uniformly distributed random number that is different in each iteration.

3.5. **Lindenmayer system.** The L-system is a fractal generation method based on string substitution [25, 26]. A fractal pattern is generated by defining a set of simple rules that iteratively replace an initial string with a more complex sequence of strings. The L-system is often used to model the branching structure of plants, as shown in Figure 3.

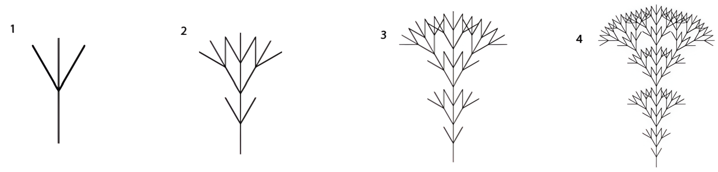

Figure 3. Branching structure of plants based on L system

Compared with these traditional fractal pattern generation methods mentioned above, the fractal pattern generation method based on genetic algorithm can carry out customised pattern generation according to user requirements and preferences. By introducing user evaluation and preference as the optimisation function of the genetic algorithm, personalised fractal pattern generation according to user needs can be achieved to meet the personalised requirements of users.

4. **Quantum genetic algorithms and improvement techniques.**

4.1. **Principles of Quantum Genetic Algorithms.**
In terms of computable problems, quantum computers can only solve problems that traditional computers can solve, but in terms of computational efficiency, due to the existence of quantum mechanical superposition, certain currently known quantum algorithms are faster than traditional general-purpose computers in dealing with the problem, thus completing the very complicated problem of solving the problem in the appropriate time.

(1) Quantum Bit Coding

The two-dimensional complex vector space defines $|0\rangle$ and $|1\rangle$ to denote two different quantum bit states, and in addition to the above two states, the state of a quantum bit can be a superposition between the above two states [27]. As the smallest unit of information, the state of a quantum bit can be represented as:

$$|\varphi\rangle = \alpha|0\rangle + \beta|1\rangle \tag{9}$$

where α and β both denote a complex number called the associated probability amplitude and satisfy the condition $|\alpha|^2 + |\beta|^2 = 1$.

Quantum bits and quantum superposition states are used to encode chromosomes in quantum genetic algorithms [28]. Each quantum chromosome is encoded as follows:

$$q_j^t = \begin{bmatrix} \alpha_1^t & \alpha_2^t & ... & \alpha_m^t \\ \beta_1^t & \beta_2^t & ... & \beta_m^t \end{bmatrix} \tag{10}$$

where t denotes the number of population generations.

The quantum population of the tth generation is denoted as $Q(t) = \{q_1^t, q_2^t, ..., q_n^t\}$, m denotes the number of quantum bits and n denotes the population size. In addition, the following normalisation conditions need to be satisfied:

$$|\alpha_i^t|^2 + |\beta_i^t|^2 = 1, i = 1, 2, ..., m \tag{11}$$

(2)Quantum Revolving Door

As the most basic operational step, quantum bits use quantum gates to perform matrix transformations to complete state migration in order to complete population evolution. Quantum bit operation generally uses quantum rotating gates [29], which are defined as follows:

$$U(\theta) = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \tag{12}$$

The process of population evolution is as follows:

$$\begin{bmatrix} \alpha_i^{t'} \\ \beta_i^{t'} \end{bmatrix} = \begin{bmatrix} \cos\theta_i & -\sin\theta_i \\ \sin\theta_i & \cos\theta_i \end{bmatrix} \begin{bmatrix} \alpha_i \\ \beta_i \end{bmatrix} \tag{13}$$

where θ_i denotes the rotation angle, and it is necessary to follow the adjustment rule to specify the angle and direction of θ_i. The coordinates of the quantum revolving door are schematically shown in Figure 4.

(3) Quantum crossover and mutation

The quantum crossover operation is a fully perturbative crossover operation based on the coherence property of quanta. For a quantum crossover operation, each quantum chromosome in the population is required to implement the crossover operation. If the population number is 6 and the chromosome length is 7, a crossover operation with diagonally rearranged combinations is given in Table 1.

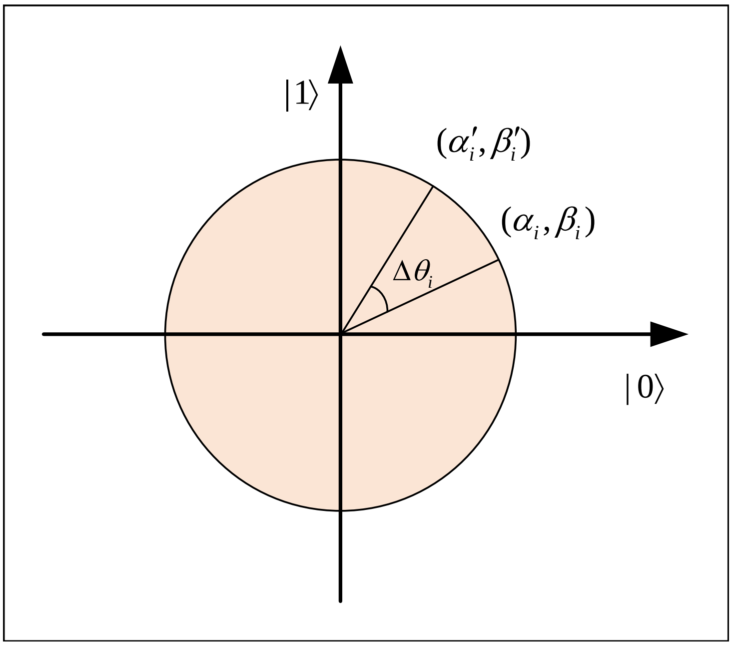

Figure 4. Schematic diagram of the quantum revolving door

Table 1. Full interference cross

No.	**Interference cross**						
1	A	E	D	C	B	A	E
2	B	A	E	D	C	B	A
3	C	B	A	E	D	C	B
4	D	C	B	A	E	D	C
5	E	D	C	B	A	E	D

In the quantum variation operation, the quantum genetic algorithm uses the quantum variation operator $U(\omega(\Delta\theta_i))$ to achieve update optimisation.

$$U(\omega(\Delta\theta_i)) = \begin{bmatrix} \cos(\omega(\Delta\theta_i)) & -\sin(\omega(\Delta\theta_i)) \\ \sin(\omega(\Delta\theta_i)) & \cos(\omega(\Delta\theta_i)) \end{bmatrix} \tag{14}$$

$$\omega(\Delta\theta_i) = f(\alpha_i, \beta_i) * \Delta\theta_i \tag{15}$$

where $f(\alpha_i, \beta_i)$ denotes the direction of rotation, $\Delta\theta_i$ denotes the magnitude of the rotation, and Δ denotes the adjustment factor (which generally takes on a small value).

4.2. **Improved quantum genetic algorithm.** The improvements in this paper are divided into two main areas:

Firstly, since the small habitat co-evolutionary strategy based on probability partitioning can effectively solve the optimisation problem of multivariate continuous function, this paper introduces the small habitat co-evolutionary strategy in the initialisation process of the population, which is conducive to maintaining the diversity of the population and easier to find the optimal solution. Then the initial quantum level is calculated as follows:

$$\begin{bmatrix} \alpha_k \\ \beta_k \end{bmatrix} = \begin{bmatrix} \sqrt{\frac{i}{N+1}} \\ \sqrt{\frac{1-i}{N+1}} \end{bmatrix} \tag{16}$$

where i denotes the ordinal number of the subpopulation and N denotes the total number of subpopulations.

Secondly, as mentioned earlier, the adjustment of quantum chromosomes needs to be done via $U(\theta_i)$ according to the quantum rotating gate adjustment rule in order to complete the population evolution. In this paper, a new quantum rotating gate adjustment rule, as shown in Table 2, is designed in order to process the quantum rotation angle in real time, which improves the convergence speed of the quantum search and increases the diversity of the population. It can be seen that the main idea is that the current individual needs to implement the evolutionary process towards the optimal individual in any state. Where x_i is the i-th position of the current chromosome, b_i is the i-th position of the current optimal chromosome, and $f(\cdot)$ is the fitness function. The quantum revolving door $U(\theta_i)$ is updated as shown in Equation **??**.

Table 2. Quantum revolving door adjustment rule

x_i	b_i	$f(x_i) \geq f(b_i)$	$\Delta\theta_i$	$s(\alpha_i, \beta_i)$		
				$\alpha_i\beta_i > 0$	$\alpha_i\beta_i < 0$	$\alpha_i = 0, \beta_i = 0$
0	0	False	δ	-1	+1	0
0	0	True	δ	-1	+1	0
0	1	False	δ	+1	-1	0
0	1	True	δ	-1	+1	0
1	0	False	δ	-1	+1	0
1	0	True	δ	+1	-1	0
1	1	False	δ	+1	-1	0
1	1	True	δ	+1	-1	0

5. **Decorative fractal pattern generation based on improved quantum genetic algorithm.** Fractal pattern generation based on genetic algorithms belongs to the class of evolutionary algorithms. Evolutionary algorithms are a class of heuristic optimisation algorithms based on biological evolution and heredity, of which genetic algorithms are the most widely used type of evolutionary algorithms. Genetic algorithms optimise and search for candidate solutions by simulating the process of biological evolution through operations such as selection, crossover and mutation.

In decorative fractal pattern generation based on improved quantum algorithm, the fractal pattern can be regarded as an individual (i.e., chromosome) in the genetic algorithm, and the process of fractal pattern generation can be regarded as an objective function in the optimisation process. The advantages and disadvantages of each individual are measured by the fitness function, and the selection, crossover and mutation operations are performed on the individuals to continuously evolve to generate new individuals until a satisfactory fractal pattern is achieved.

Decorative Fractal Pattern Generation Based on Improved Quantum Genetic Algorithm is a method that uses a combination of quantum genetic algorithm and decorative techniques to generate fractal patterns with decorative effects. Specifically, the computational process of the method is as follows:

Step 1. Encoding: the fractal pattern is represented as an encoding of the chromosome, using binary or floating point encoding to represent the parameters and structure of the fractal pattern.

Step 2. Initialise population: randomly generate an initial population of chromosomes representing different fractal patterns.

Step 3. Fitness function: Define the fitness function to evaluate the quality and decorative effect of each individual (fractal pattern). In this paper, the design of the fitness function takes into account the aesthetics, symmetry and decorative effect of the fractal.

(1) Aesthetic assessment F_1 Define an aesthetics factor that is evaluated based on factors such as the overall shape of the fractal pattern, the smoothness of the curves, and the proportions. The aesthetics score is calculated using curve fitting by mapping the aesthetics factor to a suitable score range, for example between 0 and 1.

(2) Symmetry assessment F_2 Consider the symmetry of a fractal pattern, which is assessed using the number of symmetry axes or the degree to which the symmetry features match each other. Similarly, the symmetry score is calculated herein by mapping the symmetry factor to a suitable range of scores.

(3) Evaluation of decorative effects F_3 Define some decorative features such as texture of patterns, complexity of shapes, richness of lines, etc. Use subjective scoring to get the decorative effect factor and map it to an appropriate score range.

For the above assessment items, the scores can be calculated separately according to the importance and weight, and then the scores can be combined to get the composite adaptation score. In this paper, we weight and sum the scores according to specific needs. These specific needs can be adjusted at any time according to the different demand tendencies of customers. Therefore, the calculation equation of the adaptability function can be defined as:

$$fitness = w_1 * F_1 + w_2 * F_2 + w_3 * F_3 \tag{17}$$

where w_1, w_2, and w_3 are the weights of each assessment item to balance the importance of each assessment.

Step 4. Quantum encoding: the chromosome is quantum encoded to map the values of the chromosome to quantum bits.

Step 5. Quantum initialisation: quantum initialisation of quantum-encoded chromosomes to generate initial quantum states as populations.

Step 6. Selection: use a selection operation (e.g., quantum measurement) to select a subset of individuals as parents based on the probability distribution of quantum states.

Step 7. Quantum crossover: quantum crossover operation is performed on selected parents to achieve chromosome crossover through the action of quantum gates.

Step 8. Quantum mutation: a quantum mutation operation is performed on the newly generated chromosome, introducing operators such as quantum spinning gate or quantum annealing to introduce random changes.

Step 9. Inverse Quantum Coding: inverse quantum coding of the quantum coded chromosome to map the quantum bits back to the chromosome values.

Step 10. Iteration: Repeat quantum selection, quantum crossover and quantum mutation operations to continuously generate new individuals until the specified number of iterations is reached or the termination condition is satisfied.

Step 11. Result: the individual with the highest fitness is selected as the final generated decorative fractal pattern.

By combining the properties of quantum computing with genetic algorithms, it is possible to take full advantage of quantum parallelism and quantum iteration to improve the efficiency of search and optimisation. At the same time, the combination of decorative techniques can increase the decorative effect and complexity of the generated fractal pattern. Through the iterative optimisation process of quantum genetic algorithm, individuals approaching the target fractal pattern can be gradually generated, and the quality and characteristics of the generated fractal pattern can be continuously improved by selection and mutation operations.

6. Experimental results and analyses.

6.1. Experimental setup. In order to verify the advantages of the proposed improved quantum genetic algorithm even further, it was tested against the Quantum Particle Swarm Algorithm (QPSO) [30], and the Two-dimensional Quantum Genetic Algorithm (2D-QGA) [31]. The experimental parameters were configured as follows: the number of populations was 100, the maximum number of iterations was 200, and the number of quantum bits was 10 (the encoding of fractal patterns needs to be represented using 10 quantum bits). Hadamard gates were selected for quantum crossover and quantum mutation operations. Hadamard gate [**?**] is selected for initialisation operation and CNOT gate for quantum crossover operation. The quantum mutation operations are CNOT gate and single-bit rotation gate. The rotation angle chosen in this paper is $\pi/2$.

According to the actual needs and design objectives of wall decorations, the weights of the adaptability function and the specific evaluation methods are set. The weight of the aesthetics factor $w_1 = 0.4$, the weight of the symmetry assessment $w_2 = 0.3$, and the weight of the decorative effect assessment $w_3 = 0.3$.

6.2. Function processing performance test. In order to verify the convergence and optimisation ability of the algorithms proposed in this paper, the above three algorithms are used to optimise five typical continuous complex functions, namely: Sphere function, Rosenbrock function, Rastrigin function, Griewank function and Ackley function, as shown in Figure 5. Comparing the results, it can be seen that compared with QPSO and 2D-QGA, the results obtained by the proposed algorithms in this paper are one or two orders of magnitude higher, that is to say, avoiding the population from falling into the local optimal solution, and improving the accuracy and efficiency of fractal pattern generation.

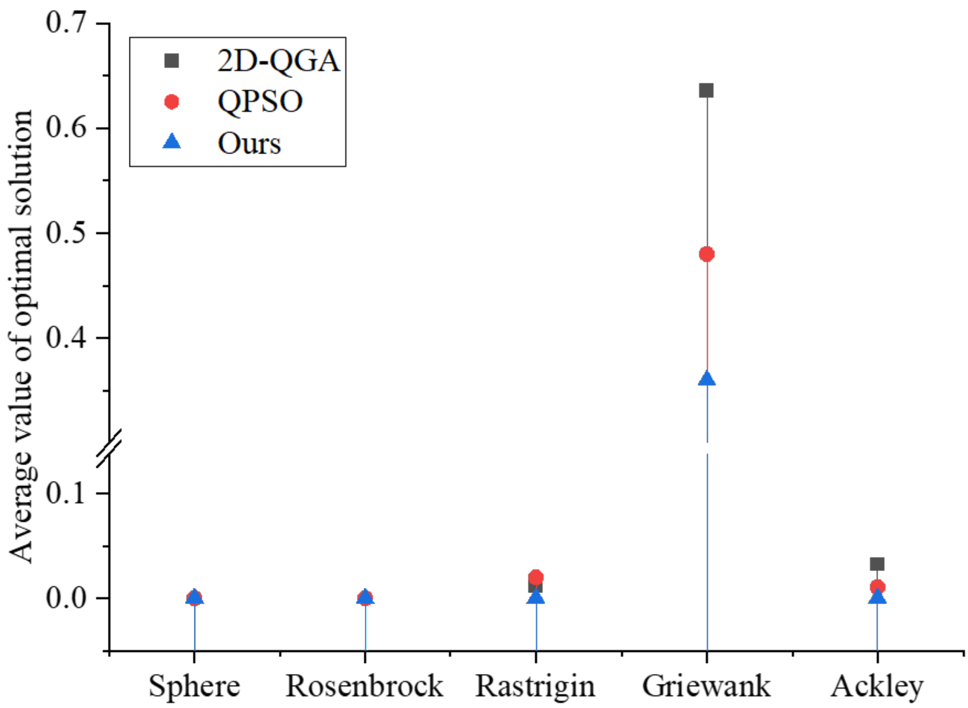

Figure 5. Test function and comparison results

6.3. **Design Example.** The wall decoration design is used as a real case to verify the feasibility of the improved quantum genetic algorithm. The wall decoration fractal patterns designed are suitable for use in a restaurant or café. The fractal patterns are required to provide a unique decorative element to enhance the aesthetics and artistry of the dining experience. The geometric shapes and details of the patterns are also required to create a modern and stylish feel for the restaurant.

In crossover and mutation operations, a retention method of fractal pattern coding was used to ensure that the characteristics of the fractal pattern and design requirements were maintained. Genetic coding was used to represent the fractal pattern. For crossover operations, the strategy of uniform crossover was used. Uniform crossover means that the crossover operation is carried out one by one at each gene position and the decision of whether or not to carry out crossover is made based on the crossover probability, thus transmitting the fractal pattern coding of the parent individual to the offspring individual. In the binary coding approach, the features of the fractal pattern are preserved by bit manipulation. For example, a mutation operation using bit operations such as bit swapping or bit flipping ensures that the mutated individual retains the features of the original individual. The generated fractal pattern for wall decoration is shown in Figure 6.

(a) Restaurants (b) Cafes

Figure 6. Generated fractal patterns for wall decorations

Taking Figure 6(b) as an example, it can be seen that the shapes and patterns in the generated patterns have similarities at all scales, i.e., similar shapes and patterns can be seen to appear whether observing the overall pattern or local details. The pattern consists of multiple layers and branches that form a complex geometric structure. The interweaving and interlacing of these branches and shapes creates a fine and interesting geometric texture. The pattern exhibits symmetry, both horizontally and vertically, as the symmetry of the shapes and patterns can be seen. The curves and shapes in the pattern give a sense of flow and dynamism, as if presenting a flowing movement of comfort and grace. Through these features, this wall decoration fractal pattern can create a unique and comfortable atmosphere for the café, which meets the case design requirements, thus verifying the effectiveness of the improved quantum genetic algorithm.

7. **Conclusions.** This work proposes the application of quantum genetic algorithm to the problem of decorative fractal pattern generation. Firstly, a new quantum rotating gate

adjustment rule is designed in order to process the quantum rotating angle in real time, which improves the convergence speed of the quantum search and increases the diversity of the population, and then a catastrophe operator based on the tournament selection mechanism is employed in order to overcome the phenomenon of prematurity. Then, a decorative fractal pattern generation method based on an improved quantum genetic algorithm is proposed, and specific implementation steps are given. A unique fitness function is designed by considering three aspects of fractals, such as aesthetics, symmetry, and decorative effect. The scores are weighted and summed according to specific needs. These specific needs can be adjusted at any time according to the different demand tendencies of customers. The results of generating fractal patterns for wall decoration in restaurant and cafe scenarios meet the case design requirements, thus verifying the effectiveness of the improved quantum genetic algorithm.

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REFERENCES

[1] B. Wohlberg, and G. De Jager, "A review of the fractal image coding literature," *IEEE Transactions on Image Processing*, vol. 8, no. 12, pp. 1716-1729, 1999.

[2] Y. Fisher, "Fractal image compression," *Fractals*, vol. 2, no. 03, pp. 347-361, 1994.

[3] M. Ghazel, G. H. Freeman, and E. R. Vrscay, "Fractal image denoising," *IEEE Transactions on Image Processing*, vol. 12, no. 12, pp. 1560-1578, 2003.

[4] M. Ivanovici, and N. Richard, "Fractal dimension of color fractal images," *IEEE Transactions on Image Processing*, vol. 20, no. 1, pp. 227-235, 2010.

[5] K. Belloulata, and J. Konrad, "Fractal image compression with region-based functionality," *IEEE Transactions on Image Processing*, vol. 11, no. 4, pp. 351-362, 2002.

[6] G. Lu, "Fractal image compression," *Signal Processing: Image Communication*, vol. 5, no. 4, pp. 327-343, 1993.

[7] M. Polvere, and M. Nappi, "Speed-up in fractal image coding: comparison of methods," *IEEE Transactions on Image Processing*, vol. 9, no. 6, pp. 1002-1009, 2000.

[8] C.-S. Tong, and M. Pi, "Fast fractal image encoding based on adaptive search," *IEEE Transactions on Image Processing*, vol. 10, no. 9, pp. 1269-1277, 2001.

[9] R. Distasi, M. Nappi, and D. Riccio, "A range/domain approximation error-based approach for fractal image compression," *IEEE Transactions on Image Processing*, vol. 15, no. 1, pp. 89-97, 2005.

[10] M.-S. Wu, W.-C. Teng, J.-H. Jeng, and J.-G. Hsieh, "Spatial correlation genetic algorithm for fractal image compression," *Chaos, Solitons & Fractals*, vol. 28, no. 2, pp. 497-510, 2006.

[11] R. Quevedo, L.-G. Carlos, J. M. Aguilera, and L. Cadoche, "Description of food surfaces and microstructural changes using fractal image texture analysis," *Journal of Food Engineering*, vol. 53, no. 4, pp. 361-371, 2002.

[12] T. Kovács, "A fast classification based method for fractal image encoding," *Image and Vision Computing*, vol. 26, no. 8, pp. 1129-1136, 2008.

[13] J. Aguirre, R. L. Viana, and M. A. Sanjuán, "Fractal structures in nonlinear dynamics," *Reviews of Modern Physics*, vol. 81, no. 1, 333, 2009.

[14] A. Fronczak, and P. Fronczak, "Biased random walks in complex networks: The role of local navigation rules," *Physical Review E*, vol. 80, no. 1, 016107, 2009.

[15] M. S. Tavazoei, and M. Haeri, "An optimization algorithm based on chaotic behavior and fractal nature," *Journal of Computational and Applied Mathematics*, vol. 206, no. 2, pp. 1070-1081, 2007.

[16] W. Pang, and K. Hui, "Interactive evolutionary 3D fractal modeling with modified IFS," *Computer-Aided Design and Applications*, vol. 6, no. 1, pp. 55-67, 2009.

[17] B. Abboushi, I. Elzeyadi, R. Taylor, and M. Sereno, "Fractals in architecture: The visual interest, preference, and mood response to projected fractal light patterns in interior spaces," *Journal of Environmental Psychology*, vol. 61, pp. 57-70, 2019.

[18] H. Chao, "The fractal artistic design based on interactive genetic algorithm," *Computer-Aided Design and Applications*, vol. 17, no. S2, pp. 35-45, 2020.

[19] R. Lahoz-Beltra, "Quantum genetic algorithms for computer scientists," *Computers*, vol. 5, no. 4, 24, 2016.

[20] A. Malossini, E. Blanzieri, and T. Calarco, "Quantum genetic optimization," *IEEE Transactions on Evolutionary Computation*, vol. 12, no. 2, pp. 231-241, 2008.

[21] U. Roy, S. Roy, and S. Nayek, "Optimization with quantum genetic algorithm," *International Journal of Computer Applications*, vol. 102, no. 16, pp. 1-7, 2014.

[22] R. Nichols, L. Mineh, J. Rubio, J. C. Matthews, and P. A. Knott, "Designing quantum experiments with a genetic algorithm," *Quantum Science and Technology*, vol. 4, no. 4, 045012, 2019.

[23] J. Xiao, Y. Yan, J. Zhang, and Y. Tang, "A quantum-inspired genetic algorithm for k-means clustering," *Expert Systems with Applications*, vol. 37, no. 7, pp. 4966-4973, 2010.

[24] T.-Y. Wu, H. Li, S. Kumari, and C.-M. Chen, "A Spectral Convolutional Neural Network Model Based on Adaptive Fick's Law for Hyperspectral Image Classification," *Computers, Materials & Continua*, vol. 79, no. 1, pp. 19-46, 2024.

[25] Y. Ma, Y. Peng, and T.-Y. Wu, "Transfer learning model for false positive reduction in lymph node detection via sparse coding and deep learning," *Journal of Intelligent & Fuzzy Systems*, vol. 43, no. 2, pp. 2121-2133, 2022.

[26] F. Zhang, T.-Y. Wu, Y. Wang, R. Xiong, G. Ding, P. Mei, and L. Liu, "Application of Quantum Genetic Optimization of LVQ Neural Network in Smart City Traffic Network Prediction," *IEEE Access*, vol. 8, pp. 104555-104564, 2020.

[27] M. Zamir, "Arterial branching within the confines of fractal L-system formalism," *The Journal of General Physiology*, vol. 118, no. 3, pp. 267-276, 2001.

[28] F. Boudon, C. Pradal, T. Cokelaer, P. Prusinkiewicz, and C. Godin, "L-Py: an L-system simulation framework for modeling plant architecture development based on a dynamic language," *Frontiers in Plant Science*, vol. 3, 21069, 2012.

[29] X. Wang, Y. Su, C. Luo, F. Nian, and L. Teng, "Color image encryption algorithm based on hyperchaotic system and improved quantum revolving gate," *Multimedia Tools and Applications*, vol. 81, no. 10, pp. 13845-13865, 2022.

[30] L.-Y. Hsu, E. Y. Li, and H. Rabitz, "Single-molecule electric revolving door," *Nano Letters*, vol. 13, no. 11, pp. 5020-5025, 2013.

[31] S. N. Omkar, R. Khandelwal, T. Ananth, G. N. Naik, and S. Gopalakrishnan, "Quantum behaved Particle Swarm Optimization (QPSO) for multi-objective design optimization of composite structures," *Expert Systems with Applications*, vol. 36, no. 8, pp. 11312-11322, 2009.

[32] S. Mondal, and A. Tsourdos, "Two-dimensional quantum genetic algorithm: Application to task allocation problem," *Sensors*, vol. 21, no. 4, 1251, 2021.

[33] C. J. Fewster, and R. Verch, "The necessity of the Hadamard condition," *Classical and Quantum Gravity*, vol. 30, no. 23, pp. 235027, 2013.