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Research Article

Illustration Design Model with Clustering Optimization Genetic Algorithm

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For the application of the standard genetic algorithm in illustration art design, there are still problems such as low search efficiency and high complexity. This paper proposes an illustration art design model based on operator and clustering optimization genetic algorithm. First, during the operation of the genetic algorithm, the values of the crossover probability and the mutation probability are dynamically adjusted according to the characteristics of the population to improve the search efficiency of the algorithm, then the k-medoids algorithm is introduced to optimize the clustering of the genetic algorithm, and a cost function is used to carry out and evaluate the quality of clustering to optimize the complexity of the original algorithm. In addition, a multiobjective optimization genetic algorithm with complex constraints based on group classification is proposed. This algorithm focuses on the problem of group diversity and uses k-means cluster analysis operation to solve the problem of group diversity. The algorithm divides the entire group into four subgroups and assigns appropriate fitness values to reflect the optimal preservation strategy. A large number of computer simulation calculations show that the algorithm can obtain a widely distributed and uniform Pareto optimal solution, the evolution speed is fast, usually only a few iterations can achieve a good optimization effect, and finally the improved genetic algorithm is used to design the random illustration art. The example simulation shows that the improved algorithm proposed in this paper can achieve higher artistic and innovative illustration art design.

1. Introduction

In the traditional art design process, if designers have inspiration and ideas, they must use tools to transfer their designs to reality, which requires human labor, so the quantity and quality of creations are limited. Moreover, multiple works cannot be produced at the same time, which is the shortcoming of the traditional creation method. Now, because computers provide the level of technology needed in the field of artistic creation, they can well help designers develop their ideas and turn them into reality in a much shorter time. It took tens of thousands of years for pictures to spread to words and thousands of years for words to spread to print. It took about 800 years from the invention of printing in the Song Dynasty to the invention of the first telegraph in the world. Since the 19th century, from photography to film and television to the Internet, each of these advances has been shrinking within 100 years [1].

Evolutionary design refers to the application of a new evolutionary computing method in the concept of computer design, which can be fully applied in the field of design. The first computer evolution program in history [2, 3] was mainly used to simulate tree groups. The theory that genetic algorithm can be used in the process of design improvement and optimization is proposed, and the theoretical framework of the whole design is explained [4, 5]. His design system could be used to make cars and seats; the use of computer-aided evolutionary design in the field of artistic innovation [6, 7] opens a new door for evolutionary art. In addition to these, some people have applied computer simulation technology to more fields, such as the lamp in art and sculpture, making the application scope of this technology more extensive. In addition, some people also applied genetic algorithm in the floor plan of the design building [8, 9]. I wrote a program called Form, which turned the evolutionary design into a three-dimensional representation for

the first time [10]. In the fields of synthesizing colors, making cartoon characters, changing fonts, and designing exterior shapes of cars, evolutionary model technology has been used, and an interactive design system has been successfully created [11, 12]. Related scholars have researched and developed computer-supported innovative design of appearance [13]. CAD is used to realize the difficult problems of color representation, design sketch, and construction pattern [14]. Cluster analysis is a commonly used method in pattern recognition and data mining. It is an effective method for knowledge discovery based on data, and it is especially suitable for situations where the number of pattern classifications is unknown [15, 16]. Cluster analysis is an unsupervised learning method that does not require any prior domain knowledge. It extracts classification criteria based on mathematical characteristics and classifies data [17]. At present, many clustering algorithms have been applied to the analysis of gene expression data. Hierarchical clustering is one of the earlier methods applied to the analysis of gene expression data. A uniformly connected hierarchical clustering algorithm is used to identify the coregulated yeast genome [18]. However, when the given gene data set changes slightly, the hierarchical clustering algorithm is easy to interfere, the clustering process lacks robustness, and the clustering results will greatly deviate. K-means clustering is another method often used for gene expression data analysis due to its good computational performance [19]. However, the k-means algorithm is easy to converge to the local optimal solution, and the clustering results are very dependent on the random initialization process of the algorithm; that is, multiple k-means clustering on the same data set may produce different clustering results [20, 21]. Self-organizing mapping is a kind of neural network, which can map data in high-dimensional space to low-dimensional space, and it is also applied to clustering analysis of gene expression data [22]. SOM's shortcoming is that unbalanced clustering results are often produced, and it is difficult to find clear classification boundaries from the clustering results. As an effective method to solve optimization problems, the evolutionary algorithm has strong global convergence and robustness, and it does not need to rely on the characteristic information of the problem, such as the gradient information such as derivative, in the process of solving the problem. The clustering analysis of gene expression data can also be reduced to an optimization problem [23, 24]. In recent years, many researchers have begun to introduce evolutionary algorithms into the clustering method of gene expression data. The fundamental strategy of this new clustering method is to simulate the evolutionary process in nature to conduct a heuristic search and find the clustering division with the optimal objective function value through the continuous evolution of the clustering solution population [25]. Among them, the most typical representative is gene clustering analysis based on genetic algorithm. According to the principle of genetic algorithm, the crossover operator in a genetic algorithm is replaced by the k-means operator, and a hybrid genetic clustering algorithm is proposed [26]. Then, on the basis of GKA, the algorithm was improved, and the incremental

genetic k-mean clustering algorithm [27] was proposed, which was applied to the clustering analysis of gene expression data and achieved good results. A phased multi-objective genetic clustering algorithm [28] for gene clustering analysis was designed. This algorithm adopted the newly proposed genetic strategy of variable string length coding and was combined with the fuzzy C-means clustering algorithm in the iterative process so as to improve the search efficiency of the genetic clustering algorithm. However, the clustering method based on genetic algorithm must carry out corresponding genetic operators in the process of clustering, such as selection, crossover, and mutation. So, the algorithm complexity is high, and the actual execution time of the clustering algorithm is often relatively long. At the same time, the greater the number of samples, the greater the dimension. The clustering problem of large-scale algorithms tends to converge to the local optimum prematurely [29, 30]. These defects restrict the application of genetic clustering algorithm in gene expression data analysis.

In order to optimize the standard genetic algorithm and improve some existing shortcomings, this paper uses a design model of illustration art, which is based on the genetic algorithm of cluster optimization and operator. Meanwhile, this model is more innovative through experimental simulation. D fitness was used to map the search space to the feasible space, and cluster analysis was used to realize the diversity of groups. The algorithm divides the whole group into four categories: infeasible group, feasible non-Pareto group, cluster Pareto group, and cluster Pareto optimal group. Different groups are assigned with appropriate R adaptive value and select operation according to this adaptive value, thus effectively solving the problem of constraint processing and adaptive value function. This algorithm uses clustering technique and classification concept, which greatly improves the performance of the algorithm, improves the quality of the understanding set, and provides an effective way to solve some highly constrained optimization problems. Computer simulation experiments show that the algorithm not only can obtain the widely distributed and uniform Pareto optimal solution but also has a fast evolution speed and usually only needs 1040 generations to achieve a good optimization effect. The first part is the introduction. The second part introduces illustration design based on genetic operator optimization. The third part carries out multiobjective clustering optimization genetic algorithm based on Pareto optimal solution illustration design. The fourth part is the example verification. The fifth part is the conclusion.

2. Illustration Design Based on Genetic Operator Optimization

2.1. Optimization of Crossover Mutation Operator Based on Dynamic Adjustment. Genetic algorithm is a method to gradually explore the excellent population. This method is realized by constantly changing the composition of the original population and creating a new population. The rate of formation of the new population will have a certain

impact on the convergence, and the main variables related to it are the probability Q_c of crossover and the probability Q_w of variation. If Q_w is too small, exploration will be slow, and if Q_w is too large, new individuals will be formed very quickly, but at the same time, the better individuals may be destroyed. If the Q_w value is too small, the speed of individual generation will be relatively slow and the Q_w value will be too large, and the algorithm will be transformed into a common algorithm of random search. Its frame diagram is shown in Figure 1.

Design an automatic $Q_c Q_w$ value for ways to solve the above problems; the solution of the basic idea is in the process of operation according to different population dynamic characteristics; and to automatically adjust the two measures of value, the crossover probability and mutation probability need according to formulae (1) and (2) the static automatic adjustment.

$$Q_c = \begin{cases} Q_{c1} - \dfrac{Q_{c1} - Q_{c2}}{f_m - f_{\text{avg}}}, & f \geq f_{\text{avg}}, \\ \\ Q_{c1}, \end{cases} \tag{1}$$

$$Q_m = \begin{cases} Q_{m1} - \dfrac{Q_{m1} - Q_{m2}}{f_m - f_{\text{avg}}}, & f \geq f_{\text{avg}}, \\ \\ Q_{m1}. \end{cases} \tag{2}$$

We can find from equations (1) and (2) that if the fitness value is not concentrated during the optimization process, the value will be reduced by itself. If the fitness values are relatively concentrated in the optimization process, then these two values will automatically increase. This method can improve the quality of the population. If the value is greater than the adaptive value of any one individual, then the value increases. The opposite is smaller, and this allows individuals from the old generation to persist into the new population.

The selection operator of genetic algorithm is established on the basis of artificial fitness evaluation, and the fitness of excellent individuals is the same. In this paper, the optimal individual preservation method and simulated annealing method are used to realize the selection operator of genetic algorithm. The optimal individual preservation method is to directly introduce the individuals with the highest fitness in the population of this generation into the population of the next generation and no longer adopt genetic operations such as crossover and mutation to them. This method ensures that the encoding of the optimal individual in each generation of the population is not destroyed and the convergence of the algorithm is guaranteed.

The simulated annealing method is to build a dynamic database of all the optimal individuals, whose selection probability changes dynamically with the increase of algebra. Because artificial selection is noisy, if the selection probability of each generation K is the same, the probability changes in echelon form. The calculation formula of probability function is as follows:

$$M(m) = \frac{m^4 + 1 - \cos(m/2)}{2}. \tag{3}$$

Taking clay sculpture illustration design as an example, the design results by using the standard genetic algorithm and the improved algorithm proposed in this paper are shown in Figure 2.

2.2. Illustration Clustering Optimization Based on K-GA. The process of selecting each group of flowers is what we call illustration art design. In the process of this design, we should classify all kinds of flowers so as to improve the efficiency of collocation and combination and avoid repeating the same style of flowers. In this paper, based on the k-medoids algorithm, the GA algorithm is improved; through the choice of random data, the algorithm can choose specific category, and it can be found in a number of clustering data of a certain number of clustering centers; then according to the difference between the center distance, the other objects can be assigned to the corresponding category. In the cost function, the distance difference between the data and the clustering center can be seen so as to judge the quality of clustering. Through the following four different cases, we can find the difference of nonclustering center T.

The K-GA algorithm takes the number of clusters K as a parameter and divides N samples into K clusters according to a certain standard (such as the distance criterion), so that the samples within the cluster have high similarity, while the samples between the clusters have low similarity. The basic process of K-GA algorithm is shown in Figure 3, and the specific solving steps are as follows:

(1) Randomly select K objects as the initial cluster center.

(2) For each object in the data set, find its distance to the center of k clusters and return to the cluster where the center of the closest cluster is located.

(3) Calculate the center point of each cluster and update k cluster centers.

(4) Repeat steps 2 and 3 until the cluster center no longer changes or the maximum number of iterations is reached.

Therefore, the specific operation process of this model is as follows:

First, if you have K flowers, the characteristic matrix of choosing these flowers for illustration art is as follows:

$$\begin{pmatrix} b_{11}, b_{12}, \ldots, b_{19} \\ \ldots \\ b_{k1}, b_{k2}, \ldots, b_{k9} \end{pmatrix}. \tag{4}$$

Second, through the application of random functions, the population matrix can be obtained, where the center of the cluster is a kind of element and the individual element is a row.
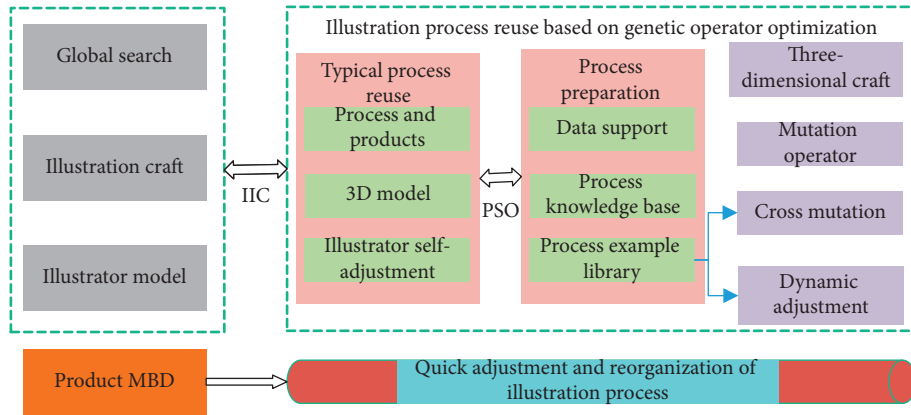
Thirdly, the fitness function is formulated:

Figure 1: Optimization of illustration design by dynamically adjusting crossover mutation operator.

(a)   (b)   (c)   (d)
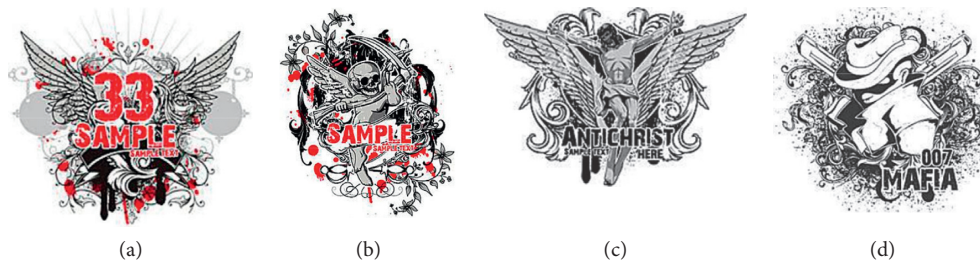
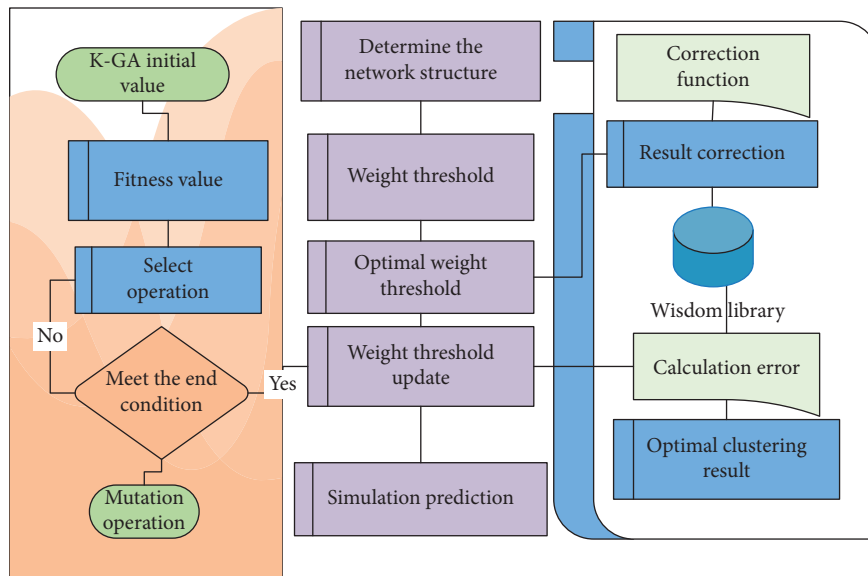Figure 2: Standard and improved fractal image illustration art design effect.

Figure 3: K-GA illustration clustering optimization flowchart.

$$E = \sum_{i=1,k} \sum |q - b_i|^2. \tag{5}$$

In the formula, E represents the sum of the mean square deviation between all the data and the corresponding cluster centers, the letter Q represents a point in one of the categories, and the symbol b represents the mean value of the cluster.

Fourth, use roulette to realize the selection operator:

$$q(b_i) = \frac{f(b_i)}{\sum f(b_i)}. \tag{6}$$

Fifth, calculate the probability of an individual continuing to the next population.

Sixth, the k-medoids algorithm is used to optimize individuals.

3. Multiobjective Clustering Optimization Genetic Algorithm Based on Pareto Optimal Solution Illustration Design

According to the basic concept of multiobjective optimization, there are essential differences between multiobjective optimization problem and single-objective optimization problem. Pareto optimal solution of multiobjective optimization problem is generally a solution set. According to Pareto, an individual is either A noninferior solution or A inferior solution; that is, A group can be divided into noninferior solution set A and inferior solution set B. Since A is A noninferior solution set and B is A inferior solution set, the probability that an individual in A is selected and passed on to the next generation in the selection process should be much higher than the probability that an individual in B is selected. In order to not only reflect the probabilistic search characteristics of the genetic algorithm but also reflect the dominance of noninferior solution set over inferior solution set, the selection operator is improved in this paper to satisfy the following principles:

(1) The preferential selection principle of noninferior solution individuals over inferior solution individuals.

(2) Probabilistic proportional selection principle within the noninferior solution set and inferior solution set.

The design scheme is as follows: according to the concept of Pareto optimal individual, each generation of the population is divided into noninferior solution set and inferior solution set. In the selection operation, the selection probability of noninferior solution individual is much higher than that of inferior solution individual, and individuals are selected in the noninferior solution set and inferior solution set by probability ratio.

First, the coding rules of the automatic clustering algorithm are based on the initialization of the random particle population; then, all the particles in the particle swarm gradually evolve as an iterative process. During each evolution, a new generation of particle population is generated at the current position of the particle based on the QPSO update operation, and the quality of the particle is evaluated through the fitness function to find the optimal solution to the current clustering problem. The evolution process continues to meet the predefined termination condition. The specific algorithm steps are described as follows:

Step 1: initialize the particles in QPSO so that each particle contains a threshold value within km range and kn cluster centers with D dimensions (initial cluster centers are randomly selected in the data set).

Step 2: the activated clustering center is determined by the threshold value in each particle, the data set is classified according to the effective clustering center of each particle, and the fitness function of each particle is calculated. The PBest population of QPSO is initialized to the current particle population, and the GBest population is initialized to the current particle with the maximum fitness value.

Step 3: the algorithm enters the cyclic iteration phase, the QPSO algorithm is used to update the particles in the population, and the clustering is reclassified according to the newly generated particles.

Step 4: if there is an empty class in the clustering result corresponding to a particle (the number of data in a class is 0), then the calculation of DB exponent will be limited. For such nonconforming particles, a number of data vectors in the data set should be randomly selected to replace the effective clustering center in the illegal particles.

Step 5: calculate the fitness function value of the population particles, update the PBest and GBest positions of the particles according to the fitness function value, and guide the evolution process of the population.

Step 6: repeat steps 3–5 until the algorithm stop criterion is met and the final clustering result is output.

In the design test of illustration model for clustering optimization, parameters of each clustering algorithm are set as follows: in the PSOAC algorithm, the acceleration constant is set as $c = 2$, and the inertia weight decreases linearly from 0.9 to 0.4 with the number of iterations of the algorithm. The contraction expansion coefficient in the QPSOAC algorithm "decreases linearly from 1.0 to 0.5 with the number of iterations of the algorithm." The population size of the three algorithms was set as 30, the number of iterations was set as 500, and the maximum clustering number was set as 20. Each algorithm was run independently 40 times for each data set. The characteristics of each data set are shown in Table 1.

Table 2 shows the optimal clustering number and the DB function value of the clustering evaluation index after the clustering division of the four data sets by three clustering algorithms. From Table 2, we can see Synthetic on the Synthetic data set, because all kinds of data within the cluster are close, the class separation between clusters is obvious, there is no data overlapping phenomenon, three kinds of clustering algorithm can accurately at a run time find the

TABLE 1: Features of cluster data set.

Data set	Number of data (N)	Data dimension (D)	Number of data classes (K)
Synthetic	65	5	4
Iris	155	6	2
Glass	216	10	5
Breast cancer	685	8	3

TABLE 2: Clustering test results of the three algorithms.

	PSOAC		ACDE		QPSOAC	
	K	DB	K	DB	K	DB
Synthetic	$3.002e + 001$	$2.237e - 001$	$3.001e + 002$	$2.234e - 001$	$3.002e + 000$	$2.234e - 001$
	$(0.03e + 001)$	$(1.204e - 004)$	$(0.04e + 001)$	$(1.312e - 003)$	$(0.05e + 000)$	$(1.185e - 003)$
Iris	$2.630e + 002$	$6.022e - 002$	$3.300e + 003$	$5.835e - 001$	$3.052e + 000$	$4.576e - 001$
	$(7.049e - 001)$	$(3.223e - 003)$	$(4.831e - 002)$	$(3.141e - 002)$	$(2.208e - 001)$	$(2.115e - 002)$
Glass	$5.801e + 002$	$1.684e + 003$	$6.205e + 000$	$1.435e + 000$	$6.082e + 000$	$1.059e + 000$
	$(4.643e - 001)$	$(6.395\ e - 004)$	$(4.799e - 001)$	$(3.038e - 002)$	$(3.497e - 001)$	$(1.473e - 002)$
Breast Cancer	$2.301e + 000$	$6.526e - 005$	$2.153e + 000$	$5.922e - 001$	$2.052e + 000$	$5.334e - 001$
	$(4.641e - 001)$	$(5.223e - 002)$	$(3.616e - 001)$	$(3.341e - 002)$	$(2.207e - 001)$	$(1.144e - 002)$

best clustering number, and the corresponding clustering evaluation is closer to the value of the DB function, explaining that the three algorithms in the data sets are good clustering results which have been achieved. For the remaining three real data sets, the overlapping of data in the data sets increases the complexity of the clustering problem, which makes the number of clustering results obtained by the clustering algorithm fluctuate to some extent in different running processes. However, the number of clustering results obtained by the QPSOAC algorithm is still the most accurate. From the DB function value corresponding to the clustering results of each algorithm, the QPSOAC algorithm can obtain the optimal DB function value on each data set, which indicates that its clustering results are superior to the other two algorithms, which further indicates that the convergence performance of QPSOAC algorithm is the best.

Figure 4 shows the comparison between the Synthetic and Iris data sets before and after the QPSOAC clustering and also indicates that the QPSOAC algorithm performs a better and more accurate classification of the data into the categories it is supposed to belong to.

4. Example Verification

In order to verify the feasibility of the algorithm, the standard genetic algorithm (GA) and the improved algorithm (K-GA) proposed in this paper are tested by using a unimodal function and a multipeak function. The average running algebraic test results of the standard genetic algorithm and the improved algorithm proposed in this paper for these two functions are shown in Table 3.

It can be seen from Table 3 that, for the two functions, when the crossover probability is 0.9, the average running algebra is the least for any test function, and the average running algebra gradually decreases with the increase of crossover probability. Therefore, the higher the crossover probability is, the greater the possibility of producing

excellent individuals will be, which improves the performance of genetic algorithm.

In order to better demonstrate the convergence of the algorithm, the iterative curves of the three algorithms in the example are compared in this paper, and the results are shown in Figure 5. It can be seen from the iteration curve of each algorithm that the traditional genetic algorithm has a poor searching ability in the late stage and is easy to fall into the local optimal. The improved genetic algorithm is not robust enough and its convergence speed is slow. However, the initial objective function value obtained by the proposed algorithm is lower, which can converge to the global optimal solution more quickly and has a better stability.

Taking illustration design in Figure 2 as an example, the design results of the standard genetic algorithm and the improved algorithm proposed in this paper are shown in Figure 6.

From Figure 6, we can find that the optimized algorithm mentioned in the paper can be used in illustration art and is innovative.

According to the data classification comparison of the Iris data set before and after DCQPSO clustering shown in Figure 7, the DCQPSO algorithm can automatically determine the number of clustering data while better dividing data into the categories it should belong to.

In order to evaluate the accuracy of the clustering results of each algorithm, we record at the end of the clustering algorithm to obtain the DB function value. Finally, the algorithm determines the optimal number of clusters, the distance between the clusters, and the distance clusters between the clusters within the cluster. The average distance between each cluster center represents the larger the distance between the corresponding clustering results, the better the effect. The average distance of vector data in the same category represents that the smaller the distance of the category, the better the corresponding clustering results. The data of these statistics are shown in Table 4.
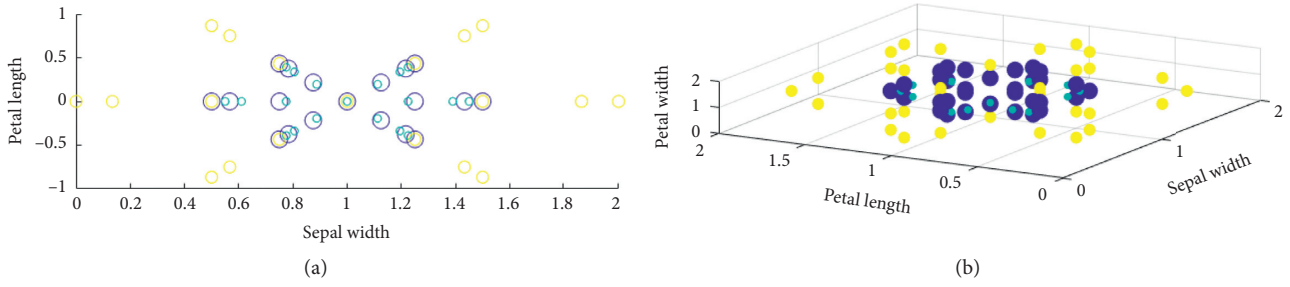
FIGURE 4: Synthetic and Iris data sets are compared before and after QPSO automatic clustering. (a) Synthetic data set and (b) Iris data set.

TABLE 3: Algorithm simulation results of test function.

Function		f_1		f_2	
		GA	K-GA	GA	K-GA
	0.9	56.26	7.34	12.65	4.74
	0.8	57.05	7.86	13.64	5.39
Crossover probability	0.7	60.07	8.06	13.86	6.38
	0.6	61.45	8.65	15.58	6.95
	0.5	62.45	9.53	19.73	7.53
	0.4	63.56	10.48	20.87	8.08
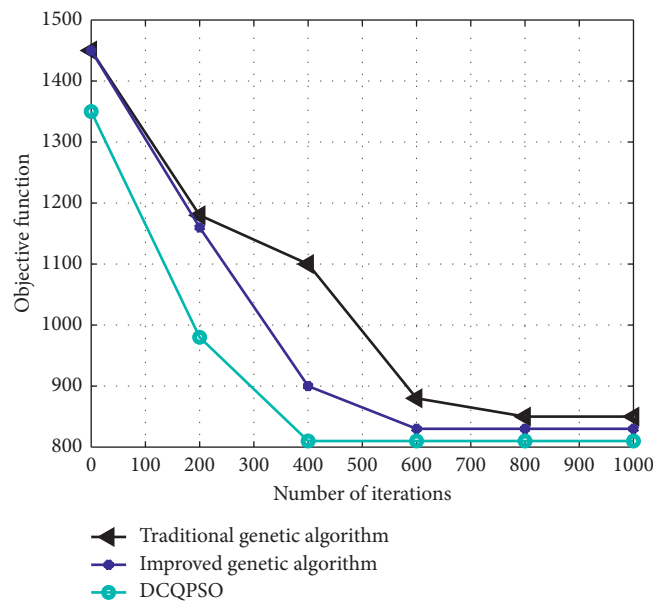
FIGURE 5: Comparison diagram of iteration curves for each example.
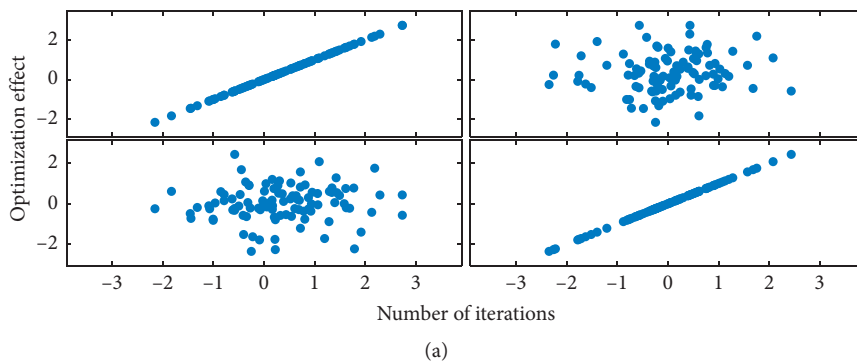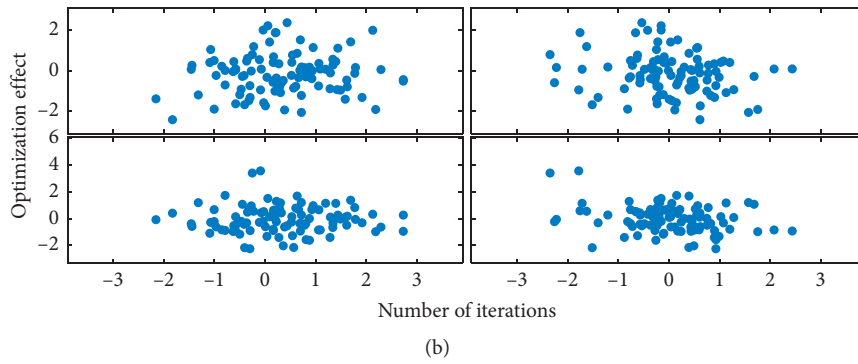

(a)

FIGURE 6: Continued.

(b)

FIGURE 6: Fractal image illustration art design of standard and DCQPSO algorithm. (a) Standard algorithm and (b) DCQPSO.
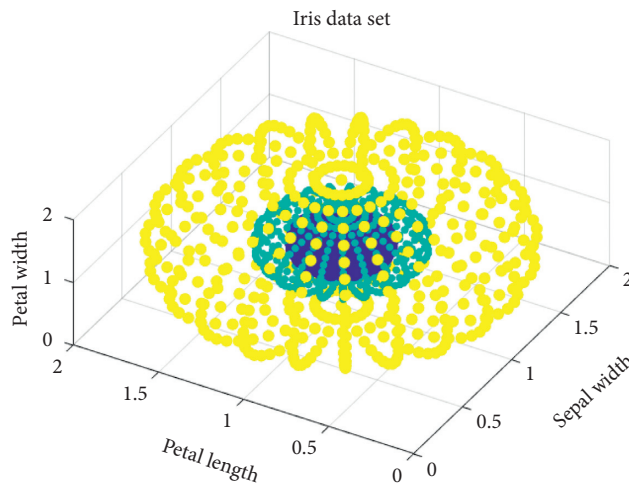

FIGURE 7: Clustering results of DCQPSO for Iris data set.

TABLE 4: Dynamic clustering results of yeast cell-384 data set.

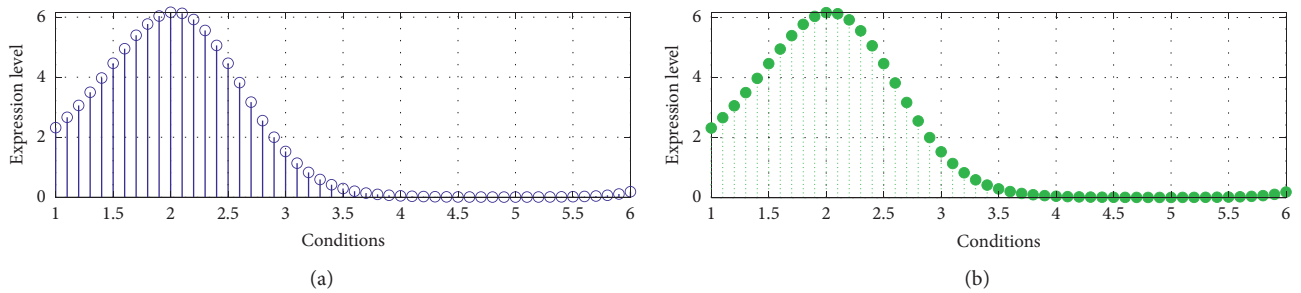| Yeast cell-384	DB	K	Intercluster distance	Intracluster distance
QPSOAC	2.708e + 000 (1.023e − 001)	5.104e + 000 (3.055e − 001)	3.726e + 000 (1.768e − 015)	6.115e + 000 (2.022e − 015)
DCQPSO	3.012e + 000 (2.034e − 001)	5.168e + 000 (3.792e − 001)	3.575e + 000 (1.557e − 015)	7.027e + 000 (4.486e − 015)

(a)

(b)

FIGURE 8: Clustering expression spectrum of DCQPSO data set.

QPSOAC algorithm and DCQPSO algorithm fully reflect their advantages in searching ability in the cluster analysis of complex data sets. It can be seen from the test results on each data set that the two dynamic clustering algorithms based on QPSO can obtain better cluster evaluation DB function value on the premise of finding the optimal cluster number of the data sets more accurately. In addition, the distance between the classes corresponding to the clustering results is larger, indicating a greater degree of separation between different classes. The smaller distance within the class indicates that the data vectors within the same class are more compact. To sum up, the dynamic clustering algorithm based on QPSO has a better effect in dealing with the clustering of gene expression data.

It can be seen from the expression spectrum of each category after clustering division of the test data set DCQPSO shown in Figure 8 that, like the clustering algorithm proposed, the DCQPSO algorithm can also well divide the gene data with similar expression patterns into the same category.

DCQPSO gene expression data clustering algorithm was presented, and with the clustering of the gene expression data set in the simulation test, the test results show that, by using the class label DCQPSO, the clustering algorithm can not only improve the convergence of the algorithm clustering optimization problem but also effectively eliminate the algorithms of particles on the direct integral operation before the information loss caused by impact on the accuracy of algorithm convergence and get better clustering results than other algorithms.

5. Conclusion

Computer technology is advancing on a global scale, and the use of evolutionary technology to help product innovation and design is an important approach. How to improve the algorithm of the computer technology and how to better use and practice the technology in the field of design have been paid more and more attention and research. In this paper, some shortcomings of some standard genetic algorithms are written out, and an experiment of the illustration art design is carried out on the basis of operator and clustering optimization genetic algorithm, which is endowed with high fitness and improves the probability of their selection. The k-means clustering analysis technique is used to realize the diversity of the population. Not only does the algorithm have high convergence but also the solution set is of high quality. The correctness and efficiency of the algorithm are verified by a large number of computer simulations. In order to solve the problem with complex constraints, the experiment shows that the optimized algorithm is more able to reflect the creativity of the design than the algorithm without optimization. Except the methods used in the paper, some of the most representative computational intelligence algorithms can be used to solve the problems, like monarch butterfly optimization (MBO), earthworm optimization algorithm (EWA), elephant herding optimization (EHO), moth search (MS) algorithm, slime mould algorithm (SMA), and Harris hawks optimization (HHO). Analysis of the

illustration of the use of color rules, exploratory analysis of its color characteristics, design for modern illustration design of the best color area ratio, and breaking the original color application rule of illustration are the focus of the next step.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest reported in this paper.

Acknowledgments

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