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Creative Transformation Strategies for Generating Decorative Patterns of Central Plains Culture Using Evolutionary Computational Modeling and AIGC Methods

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Abstract In this study, a CycleGAN framework integrating traditional pattern gene network and multi-objective evolutionary computation MOEAs is proposed, aiming at realizing the intelligent style migration and innovative design of decorative patterns of Central Plains culture. The association rules and spatial structure features of pattern design genes are extracted by constructing a traditional pattern gene network model, and MOEAs are introduced to optimize the generator weight parameters, which are combined with the channel attention mechanism to enhance the detail capturing ability. The experiments use the PASCAL VOC 2020 public dataset and the self-constructed Central Plains culture tattoo dataset ZYWY for double-benchmark validation, and the results show that the model's tattoo segmentation accuracy MIoU on PASCAL VOC 2020 reaches 86.67%, which is significantly better than that of DeepLab V3+ at 83.46%. The generated image quality FID=6.83, IS=5.34 with diversity are better than the comparison model, e.g., FID=17.92, IS=3.65 for DeepLab V3+.Ablation experiments show that removing the traditional texture gene network leads to an 8.46% decrease in MIoU and a 177% deterioration in FID, which verifies its central role in the constraints on the structure of the tattoos. The subjective evaluation showed that the application value rating P=3.52 and the innovation rating Cr=2.98 of the generated tattoos by the art design practitioners were significantly higher than that of the traditional AI generation method P=1.95 and Cr=2.74. The study provides a solution that combines both technological feasibility and artistic practicability for the digitization of traditional tattoos for inheritance and innovation.

Index Terms evolutionary computing, MOEAs, CycleGAN, channel attention mechanism, traditional tattoos

I. Introduction

Henan Province is located in the east-central part of China. Due to its proximity to the middle and lower reaches of the Yellow River and its favorable natural conditions such as hydrology and climate, it became the birthplace of the ancient Chinese civilization, and as a result, starting from the Xia Dynasty, the first hereditary dynasty of China, more than 20 dynasties have built or relocated their capitals here successively [1]-[4]. It can be said that Henan was the core area of Chinese history until the Yuan Dynasty, which confirms the saying “deer by deer in the Central Plains” [5], [6]. The "Central Plains" refers to the area of present-day Henan Province, where the "Central Plains Culture" was nurtured and radiated outward from the Henan region, which not only held an orthodox position in history for a long time, but also gradually influenced the mainstream thinking of the entire Chinese nation, becoming the root and cradle of the birth of Chinese civilization [7]-[10].

The culture of the Central Plains not only has a long history and a long history, but also has a wide range of contents and diversified types [11]. When doing the detail design of modern architecture in Henan region, the teacher should reorganize and purify the historical and cultural elements with typical local characteristics of the Central Plains, and explore the connotation and symbolism of the Central Plains culture in this figurative [12]-[14]. For the use of the Central Plains cultural elements in architectural detail design and creation, the most important is the decorative pattern [15]. The historical and cultural development of the Central Plains in the Henan region is mainly concentrated in the ancient, Xia, Shang, Zhou, Eastern Han Dynasty to the Northern Song Dynasty, from the point of view of cultural relics and monuments unearthed in Henan during these time periods, the development of decorative patterns has also experienced an incomparably prosperous period, especially in the Spring and Autumn Period, the Shang Dynasty, the Western Zhou period of the Bronze utensils, the decorative patterns of a wide range of beautifully crafted, with a tiger pattern, fire pattern, beveled eye pattern, toad pattern, Lianzhu pattern, Thunder pattern, cicada pattern, snake pattern, cattle pattern, animal face pattern, phoenix and bird pattern, etc., reflecting the prosperity of handicraft culture in Henan [16]-[18].

In this study, a creative generation framework based on Cycle GAN network integrating traditional tattoo gene network and multi-objective evolutionary computation MOEAs is proposed. The framework extracts the association rules and spatial structure features of pattern design genes by constructing a traditional pattern gene network model, and introduces a multi-objective evolutionary algorithm to optimize the weight parameters of the generative network on the basis of the model, which ultimately realizes the intelligent style migration and innovative design of the Central Plains cultural patterns. Firstly, we propose the traditional pattern analysis method with gene network model as the core, constructing the internal and external connections of gene clusters through combined frequency analysis and Wald clustering, combining Pareto's law and the nine-level scale method to unify the correlation degree calibration, and forming the pattern gene network model with self-organized characteristics. The basic principles of evolutionary computation are also systematically elaborated, focusing on the adaptation of multi-objective evolutionary algorithms MOEAs in solving the multi-objective optimization problem of texture generation, including the key techniques of non-dominated sorting and congestion operator, which provide theoretical support for the weight optimization of the subsequent style migration task. Subsequently, MOEAs are combined with generative adversarial network CycleGAN to design a multi-objective selection operator based on the channel attention mechanism, which solves the problems of missing details and lack of diversity in tattoo generation by dynamically adjusting the generator weight parameters, and realizes the accurate migration and innovative expression of traditional tattoo styles.

II. Pattern generation model based on traditional pattern gene network and multi-objective evolutionary computation

II. A. Principles of Innovative Design of Traditional Patterns

II. A. 1) Construction of traditional tattoo gene network edges

The construction of edges is a key step in gene network modeling. The edges of the gene network contain external undirected connections between genes of different gene groups and internal undirected connections between genes of the same gene group, the external connections are determined by combinatorial frequency analysis, and the internal connections are determined by calculating the Euclidean distances between genes within the same gene group by using the Wald clustering analysis method. The distance between design elements a_1, a_2, a_3 to a_n was calculated as follows:

$$d_{ij} = \sqrt{(a_{1i} - a_{1j})^2 + (a_{2i} - a_{2j})^2 + \cdots + (a_{ni} - a_{nj})^2} \tag{1}$$

where a_{ij} denotes the frequency value of the occurrence of the combination of two design elements, $i = 1, 2, 3 \cdots n$ and $j = 1, 2, 3 \cdots m$.

Combine the nine-level scaling method and Pareto's law to uniformly scale the correlation coefficient for internal and external connections respectively, denoted as r, to indicate the degree of correlation between two different gene nodes, with the larger value of r the higher the degree of correlation and the smaller value of r the lower the degree of correlation. A correlation threshold R is set, and the correlation coefficient r is larger than the threshold, then edges can be established between the two gene nodes, and finally the pattern gene network model is formed.

II. A. 2) Traditional Tattoo Gene Network Modeling

The design of traditional Chinese patterns mainly relies on the personal experience of designers, which is a chaotic system with no order. Under the driving force of “heredity”, “mutation” and “survival of the fittest”, the design genes form a kind of open system with a certain homeostatic structure. In this paper, the concept of “traditional pattern gene network” is introduced to describe the relationship between pattern design genes, and a traditional pattern gene network model is proposed based on complex network theory.

Traditional pattern gene network refers to a complex network with self-organized nature, with traditional pattern design genes as nodes, gene groups as communities and correlation between genes as edges.

Through the specification of traditional tattoo design genes, an undirected graph model $G = \{V, E\}$ of traditional tattoo gene network describing the relationship of design genes is proposed based on the principles of graph theory, where $V = \{v_1, v_2, \cdots, v_n\}$ is the set of graph genes nodes, and $E = \{e_1, e_2, \cdots, e_n\}$ is the nodes of the composition genes set, and let x_{ij} be the number of times that the graph gene vertex v_i is associated with the composition gene vertex e_j, then we obtain the association matrix of G:

$$X(G) = \begin{pmatrix} x_{11} & \cdots & x_{1m} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{nm} \end{pmatrix} \tag{2}$$

where $X(G)$ is a $[0,1]$ matrix, when $x_{ij} = 0$, it means that v_i is not associated with e_j, and when $x_{ij} = 1$ it means that v_i is associated with e_j.

The gene network model is shown in Fig. 1, the traditional tattoo gene network nodes can be divided into the tuple community and the composition community, the gene nodes of the same type within the community form an internal connection, and the gene nodes between two communities form an external connection.

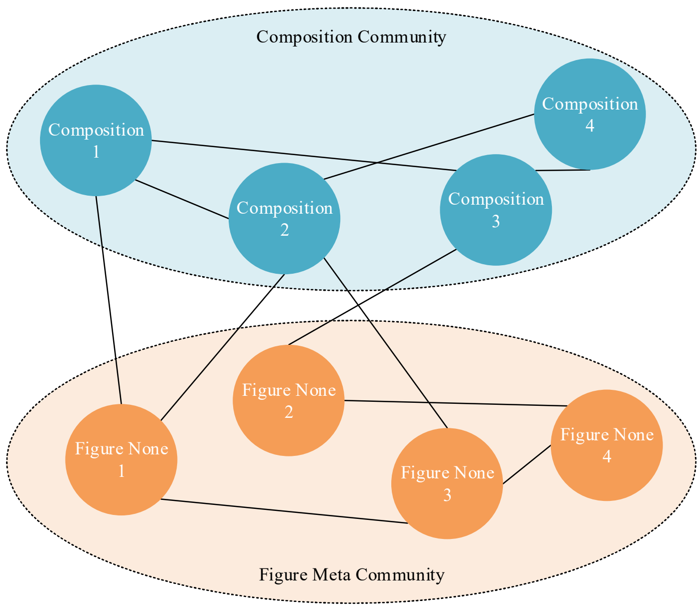

Figure 1: Traditional pattern gene network model

The construction of traditional pattern gene network model can be divided into two steps, firstly, analyze the main design genes of traditional patterns to determine the network nodes, and then establish the edges of the gene network by analyzing the correlation between the nodes, and then the computer-generated assisted design of traditional patterns can be realized by feature recognition after the formation of pattern gene network.

II. B.Evolutionary calculations

Evolutionary computation (EC) is a class of computational models and algorithms based on biological evolutionary processes in nature. It searches and optimizes the solution of a problem by simulating biological evolutionary processes such as selection, crossover and mutation. The strength of evolutionary computation lies in its global search capability for the search space and its adaptability to complex problems. Evolutionary computation can be categorized into three types according to strategies: genetic algorithms (GA), evolutionary strategies (ES), and genetic programming (EP). Their advantages are fully reflected in solving complex nonlinear single-objective optimization problems, and similarly in the field of multi-objective optimization many researchers have successively proposed multi-objective evolutionary algorithms (MOEAs).

Multi-objective evolutionary algorithms are a class of evolutionary computational algorithms for solving multi-objective optimization problems. In multi-objective problems, there are multiple conflicting objective functions, and traditional single-objective optimization algorithms cannot deal with this situation directly.MOEAs aim to find a set of solution sets, which have better performance on multiple objective functions, forming a non-dominated set of solutions called “Pareto front”.

Multi-objective optimization with optimizing n objectives takes the following form:

$$\begin{aligned} &\min F(x) = \{f_1(x), f_2(x), \cdots, f_n(x)\} \\ &s.t.\ g_i(x) \geq 0 (i = 1,2,\cdots,k) \\ &h_j(x) = 0 (j = 1,2,\cdots,m) \end{aligned} \tag{3}$$

where x is a solution in the solution space, $f_i(x)$ is the i th minimization objective, and $g_i(x)$ and $h_j(x)$ represent the constraints that need to be satisfied by the solution space.

Some key concepts about the existence of Pareto frontiers are introduced as follows:

Pareto Frontier: A Pareto frontier is the set of solutions to a multi-objective optimization problem in which no more objective function can be improved without compromising other objective functions. This means that none of the solutions in the solution set can be improved, but only improved on one objective while compromising the others.

Undominated Sorting: MOEAs use an undominated sorting method to sort the solutions to determine the solutions on the Pareto front. Each solution in the solution set is assigned a rank, called the domination hierarchy, and solutions belonging to the same rank are not dominated by each other on multiple objectives.

Crowding Degree Operator: in order to increase the diversity of the solution set, MOEAs usually introduce a crowding degree operator to measure the tightness of the distribution of solutions in the Pareto front. This helps to maintain the balance and diversity of the solution set.

The main steps of the evolutionary algorithm are divided into encoding, population initialization, selection, cross-mutation, and environment selection, which are described below:

(1) Coding

Coding refers to generate a digitized code for a solution in a certain way, the code formed by different solutions is different, and the code can also be restored back to the solution according to a certain decoding method. Only by first setting up a good coding scheme can subsequent selection, genetic manipulation, etc., be made to work.

(2) Population initialization

Population initialization means that a set of solutions is first generated according to the predefined coding scheme as the initial population. In order to enhance the search ability of the algorithm, the distribution of the initial solutions should be as uniform and wide as possible, which helps to better search for the global optimal solution.

(3) Selection

Selection needs to be performed first before population updating, which is used to identify crossover and variant parent individuals. In nature, individuals with greater genetic differences have a higher probability of successful reproduction, while reproduction of genetically similar individuals tends to lead to the degenerative phenomenon of inbreeding. In evolutionary algorithms, crossover by genetically similar individuals is inefficient and difficult to generate new solutions, while offspring from genetically more different individuals may cause the algorithm to not converge easily. By calculating the crowding degree of individuals in the population, individuals with large differences can be retained as much as possible to improve the diversity of the population.

(4) Crossover variation

Crossover is the combination of the genes of two parent individuals to produce a new solution. The crossover operation should inherit the excellent genes of the parents as much as possible, and discard the genes that are not excellent, so the crossover is not carried out on all individuals of the population, and the excellent individuals are generally selected. Mutation refers to the random mutation of genes according to a certain probability for the solution generated by crossover to maintain the diversity of the population, which helps to jump out of the local optimal solution.

(5) Environmental selection

Environmental selection simulates the process of natural organisms adapting to their environment, defining a rule used to select individuals better adapted to the current environment so that they can survive to pass on their good genes. Usually the fitness evaluation function is used to evaluate the individuals and select the best ones or eliminate the poor ones.

II. C.Weight Optimization of Evolutionary Networks on Style Migration Tasks

The introduction of multi-objective evolutionary algorithms (MOEAs) provides an efficient solution path for the multidimensional optimization problem of pattern generation. However, traditional MOEAs often face convergence difficulties due to the complexity of the generative network with high-dimensional weighting parameters when applied to the style migration task. For this reason, targeted weight optimization strategies need to be further designed by combining the structural properties of deep generative models.

II. C. 1) Selection mechanisms

The selection operation selects good individuals from the old population with a certain probability to form a new population. The multi-objective evolutionary algorithms MOEAs are used in this vignette to act as selection operators to retain the candidate individuals with higher fitness into the new population. First, the percentage of the fitness value of each candidate generator individual to the sum of the fitness values of all individuals is calculated, and the candidate pool $\hat{G}_1$ is calculated as shown in Equation (4):

$$p_1^k = \frac{\mathrm{F}_1{}^k}{\sum_{k=1}^{K} \mathrm{F}_1{}^k} \tag{4}$$

where $\mathrm{F}_1{}^k$ is the k th candidate individual in the candidate pool $\hat{G}_1$; similarly, the candidate pool $\hat{G}_2$ is computed as shown in Equation (5):

$$p_2^k = \frac{\mathrm{F}_2{}^k}{\sum_{k=1}^{K} \mathrm{F}_2{}^k} \tag{5}$$

where $\mathrm{F}_2{}^k$ is the k th candidate individual in the candidate pool $\hat{G}_2$. The roulette wheel is then divided into K intervals based on the percentage of fitness values of each candidate individual, while a random number is generated within the range of fitness sum values, and the individual corresponding to the roulette wheel interval into which the random number falls is selected.

II. C. 2) Channel Attention Module Design

Although the high-adaptive individuals screened based on the multi-objective selection mechanism can improve the optimization efficiency of the population, its specific implementation in the generative network still needs to rely on the dynamic capturing ability of the channel attention mechanism for key features.

In neural networks, the higher the dimension, the higher the number of channels, screening useful channel information is difficult for deep neural networks, therefore, the channel attention mechanism becomes an important tool for processing important channel information. The channel attention mechanism captures important features by filtering channels with high correlation with key features, which can effectively solve the problem of missing important details of images generated by generative adversarial networks. In order to let the channel attention mechanism give full play to its ability to capture important features effectively, this method adds the channel attention mechanism module to the neural network layer with the largest number of channels in the Cycle GAN generator network, and the structure of its channel attention mechanism is shown in Fig. 2. Input the feature F with height H, width W, and number of channels C, firstly, global average pooling and maximum pooling of spatial dimensions are carried out respectively to obtain two channel vectors of $1 \times 1 \times C$; then it is inputted into a two-layer multilayer perceptual machine (MLP) neural network, and then after a $sigmoid$ activation function σ. The channel weight F_c with dimension $1 \times 1 \times C$ is obtained; finally the channel weight F_c and the input feature F are multiplied element-by-element to obtain the new feature $\overline{F}$.

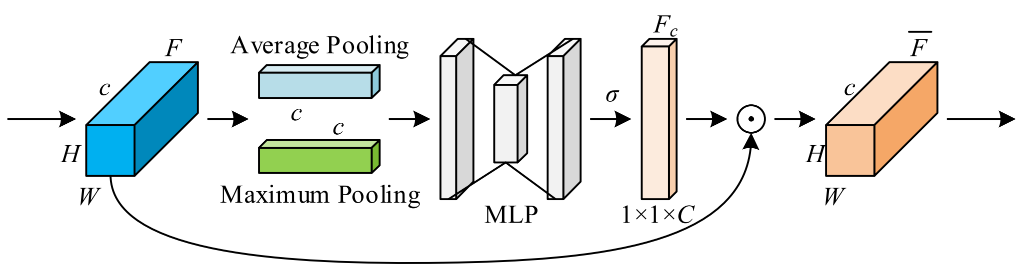

Figure 2: Channel attention mechanism structure

III. Experimental Analysis and Evaluation of Central Plains Cultural Pattern Generation Model Based on Dual Dataset Validation

Based on the construction of the theoretical framework of traditional tattoo gene network and multi-objective evolutionary computation, this chapter will further validate the practical performance of the model in the tattoo generation task through experiments. Through the dual-benchmark validation strategy of integrating the PASCAL VOC 2020 public dataset with the self-constructed Central Plains cultural tattoo dataset ZYWY, the model's comprehensive performance in tattoo segmentation accuracy, diversity of generation quality, and artistic innovativeness is systematically evaluated by combining the multidimensional evaluation metrics (MIoU, FID, and IS) with ablation experiments.

III. A. Data set construction and experimental design

III. A. 1) Data sets

The dataset I chosen for the experiment is the semantic segmentation part of PASCAL VOC 2020. This dataset, as a publicly available benchmark dataset, is mainly used to validate mainstream computer vision tasks such as image categorization, detection and semantic segmentation, and at the same time provides a perfect way to compare the metrics. The dataset contains 1 background category and 20 object-object categories, which contains 2037 test cases, 2103 sets of training cases, and 1872 sets of validation cases. In order to obtain more usable training data, this experiment generates an additional 8000 sets of training data based on the data enhancement method; dataset Ⅱ is a self-constructed ZYWY database of Central Plains Cultural Decorative Patterns, which contains a total of 4,000 Central Plains Cultural Decorative Patterns and is expanded using data enhancement. However, compared with the PASCAL VOC 2020 dataset, the volume of self-constructed basic data is not sufficient, so only the training cases and test cases are divided according to 9:1, and the validation cases are not used, which is a strategy mainly used for the small dataset, and its purpose is to ensure sufficient training cases.

III. A. 2) Experimental configuration

The CPU of the device selected for this experiment is Intel(R) Core (TM) i5-9300H CPU @ 2.40 GHz, GPU NVIDIA Ge-force GTX 2080Ti; the operating system used is UBUNTU, and the network framework is Pytorch1.7.

III. A. 3) Evaluation indicators

The evaluation metric I used in this experiment is MIoU, which focuses on calculating the intersection and concatenation ratio of the set of two corresponding pixel points of the true and predicted labels for each category, and then averaging them over all categories. The value of this metric is taken in the form of probability, so the range is set to [0,1]. Where the larger the intersection and merger ratio indicates the more accurate segmentation of the image, the formula for this metric is as follows:

$$MIoU = \frac{1}{k+1} \times \sum_{i=0}^{k} \frac{P_{ii}}{\sum_{j=0}^{k} P_{ij} + \sum_{j=0}^{k} P_{ji} - P_{ii}} \tag{6}$$

k: denotes the total number of category labels in the dataset; Pii: denotes the number of pixels assigned to the ith category label; Pij: denotes the number of pixels assigned to the ith category label, i.e., predicting the ith category to be a j-category; and Pji: denotes the number of pixels predicting all j-categories to be ith category labels.

Evaluation metrics II are the model inference speed and the number of model parameters. It is mainly used to evaluate the migration characteristics and generalization ability of the model.

Evaluation metrics III: The clarity, diversity and text-image matching of the generated images are objectively evaluated using the distance score FID and the initial score IS, which are widely used in the evaluation of image generation models.

FID is used to measure the similarity between the generated images and the real images by calculating the Freechet distance between the generated images and the real image distributions in the feature space of the pre-trained network. the lower the value of FID, the higher the similarity between the generated images and the real images, and the better the quality of the images.

IS is a metric used to measure the diversity and quality of the generated images by calculating the KL dispersion between the conditional class distribution (generated images) and the marginal class distribution (real images) using the pre-trained model.Higher IS value indicates better realism and diversity of the images from the generated model.

III. A. 4) Training strategies

Training strategy: the training strategy is the regularization method, because the neural network is more complex and strong fitting ability, it is easy to produce overfitting on the training data. Therefore, certain regularization methods are needed to improve the generalization ability of the network when training neural networks. The experiment sets up a training strategy based on the panoramic segmentation method, using the stochastic gradient descent (SGD) algorithm with a weight decay of 1×10-4, a base learning rate of 0.1, a momentum of 0.9, and a number of training iterations of 300, which is used for all the models involved in the experiment.

III. B. Pattern Segmentation Study

After completing the detailed delineation of the experimental configuration and dataset, this section focuses on the performance validation of the model in the tattoo segmentation task. By comparing the MIoU values of mainstream semantic segmentation frameworks such as PSPNet and DeepLab V3+, combined with the loss function convergence trend analysis, we quantify the advantages of the model in the feature extraction and detail preservation of texture structure.

III. B. 1) Image Semantic Segmentation Model Accuracy Comparison Experiments

Relevant experiments are conducted on the PASCAL VOC 2020 dataset to compare with different semantic segmentation frameworks, including PSPNet, FCN, DeepLab family of frameworks, and so on. The image semantic segmentation model accuracy comparison is shown in Fig. 3.

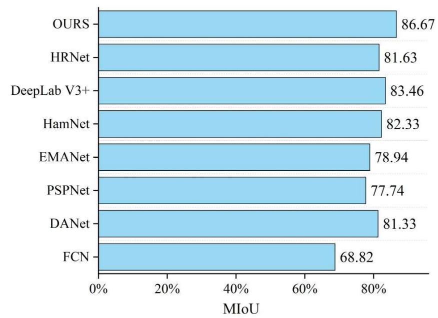

Figure 3: Accuracy comparison of image semantic segmentation models

Image Semantic Segmentation Model Accuracy Comparison demonstrates the intersection and ratio MIoU performance of different models on PASCAL VOC 2020 dataset. Traditional models such as FCN with 68.82%, PSPNet with 77.74% vs. DeepLab V3+ with 83.46% show some segmentation capability, but the model proposed in this paper significantly outperforms all the compared models with an MIoU value of 86.67%, which is an improvement of 3.21 percentage points compared to the second place DeepLab V3+. This result indicates that the generator network integrating the multi-objective evolutionary algorithm and the channel attention mechanism is more adaptive in capturing the details and spatial structure of the tattoos, which effectively improves the accuracy of semantic segmentation.

III. B. 2) Loss function

Meanwhile, the loss value change curve of the GycleGAN generator network, which incorporates the multi-objective evolutionary algorithm and the attention module in this paper, on the training data is shown in Fig. 4, which shows that the loss value decreases rapidly in the early stage and eventually stabilizes in the range of the 0.03 interval, thus reflecting the fact that the network can accurately and quickly find the direction of gradient descent.

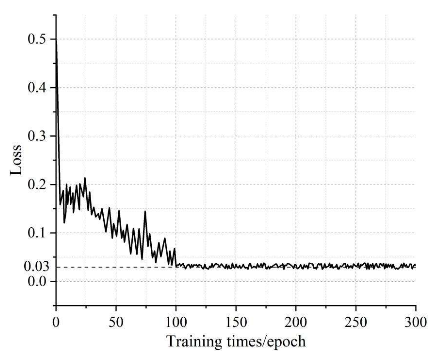

Figure 4: The loss value of the model network changes

III. C. Ablation experiments

In order to validate the impact of the core components of the model (traditional tattoo gene network, multi-objective evolutionary algorithm, channel attention mechanism, CycleGAN framework) on the generative effect and to quantify the contribution of each module. A series of ablation experiments were conducted. The ablation experiment groups are set up as follows.

Experimental group 1: Remove the traditional pattern gene network. Model variant: directly use the original CycleGAN without constructing the gene network.

Experimental group 2: Remove multi-objective evolutionary algorithms (MOEAs). Model variant: optimize generator weights using stochastic gradient descent (SGD) and remove multi-objective optimization for MOEAs.

Experimental group 3: Removal of the channel attention mechanism. Model variant: removal of the channel attention module from the generator.

Experimental group 4: Replace CycleGAN framework. Model variant: use DCGAN framework instead of CycleGAN, remove cycle consistency constraints.

Experimental group 5: Combined removal of gene networks and MOEAs. Model variant: removal of both gene networks and MOEAs, retaining only the base CycleGAN.

The evaluation indexes are MIoU stripe segmentation accuracy, FID, IS image quality value, and training convergence speed, i.e., reflecting the decreasing trend of loss function. The results of the ablation experiments are analyzed as shown in Table 1.

Table 1: Ablation experiment results

	MIoU	FID	IS	Convergence rate
Complete model	86.67	6.83	5.34	Fast and stable (0.03)
Group 1	78.21 ↓	18.95 ↑	3.62 ↓	Large fluctuations
Group 2	82.34 ↓	15.41 ↑	4.17 ↓	Slow convergence
Group 3	84.12 ↓	9.76 ↑	4.85 ↓	Stable but with limited accuracy
Group 4	65.43 ↓	32.58 ↑	2.11 ↓	Non-convergence
Group 5	70.89 ↓	27.14 ↑	2.94 ↓	Severe fluctuation

By analyzing the metrics of each ablation group, it can be seen that the gene network is the core of the pattern structure constraints, with MIoU decreasing by 8.46% and FID deteriorating by 177% after removal; MOEAs significantly improve the generation diversity, with IS decreasing by 28%, and its multi-objective optimization ability is crucial for detail retention; the channel attention mechanism contributes significantly to feature capture, with IS decreasing by 9.2% after removal, but MIoU has less impact (2.55%), indicating its low dependence on global structure; CycleGAN framework has irreplaceable cyclic consistency constraints, and replacing it with DCGAN leads to generative collapse and a 377% rise in FID; Module synergy: the performance of the gene network and MOEAs is close to that of the baseline model after their joint removal, verifying that the two are indispensable.

III. D. Evaluation and Analysis of Pattern Image Generation Results

After completing the quantitative analysis of the ablation experiment, this section develops a comprehensive evaluation from the perspectives of generated image quality and artistic value. Through the comparison of FID-IS metrics, cosine similarity heat map visualization, and multi-dimensional subjective questionnaire survey, the practical application potential of the model in the migration of Central Plains cultural pattern styles and innovative design is comprehensively verified.

III. D. 1) Analysis of FID and IS value indicators

Table 2 shows the FID and IS values for each model on the PASCAL VOC 2020 dataset and the ZYWY dataset, FID is the original measure of similarity between the generated image and the real image, and IS is used to measure the diversity and quality of the generated image.

Table 2: The FID and IS values on the PASCAL VOC 2020 and ZYWY dataset

Model	PASCAL VOC 2020		ZYWY	
	FID	IS	FID	IS
FCN	30.53	2.41	36.28	2.94
DANet	27.75	3.09	31.57	3.48
PSPNet	25.38	2.88	29.27	3.62
EMANet	24.09	3.79	26.62	4.06
HamNet	20.85	2.97	24.27	3.14
DeepLab V3+	17.92	3.65	20.39	4.19
HRNet	15.19	3.92	18.57	4.03
OURS	6.83	4.66	8.19	5.34

Table 2 evaluates the performance of each model in terms of quality and diversity of generated images. On the PASCAL VOC 2020 dataset, the FID value of this paper's model is 6.83, which is much lower than that of other models, such as the 17.92 of DeepLab V3+, and the IS value reaches 4.66, which indicates that its generated images are highly close to the real image distribution and have the best diversity and realism. On the self-constructed Central Plains cultural tattoo dataset ZYWY, the model in this paper also performs well, with a FID of 8.19 and an IS of 5.34, which further validates the model's generalization ability in the cultural tattoo generation task. It is worth noting that although models such as HamNet and DeepLab V3+ perform better in segmentation accuracy, their FID values of 24.27 and 20.39, respectively, along with IS values of 3.14 and 4.19 are significantly lower than that of OURS, indicating that it is difficult for traditional models to balance quality and diversity in the generation task.

The FID and ID values are presented by 2D scatter plots, and Figs. 5 and 6 show the FID-IS 2D scatter plots for each model on the datasets PASCAL VOC 2020 and ZYWY, respectively.

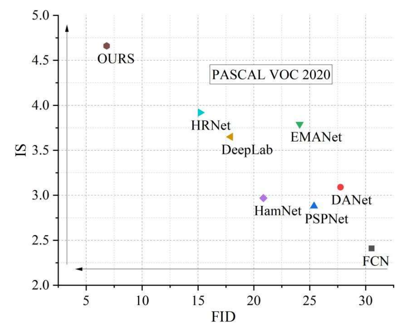

Figure 5: Scatter plots of FID-IS for each model on PASCAL VOC 2020

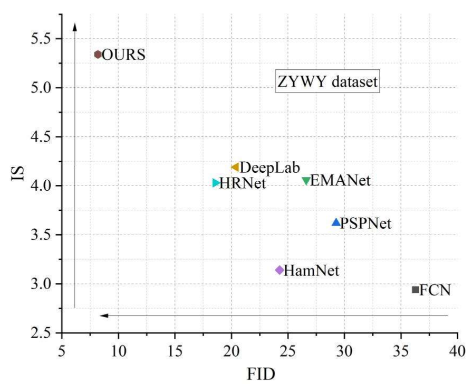

Figure 6: Scatter plots of FID-IS for each model on ZYWY dataset

The optimal state is high IS and low FID, which indicates high similarity between the model-generated image and the real image, good image quality and better realism and diversity, corresponding to upward to the left in the scatterplot. However, quality and diversity are often difficult to be achieved by both, and it is hard for any model to achieve them, so we would like to have as high a diversity as possible under the premise of excellent quality of model generation, i.e., as upward as possible under the premise of leftward in the scatterplot. Our model achieves this effect, having good diversity with the highest quality.

III. D. 2) Objective similarity evaluation analysis

Three types of images with different structures are randomly selected from the images generated by the model in this paper about the decorative patterns of the Central Plains culture. On the objective similarity evaluation, the cosine similarity algorithm is used to compare and analyze the generated images with the sample images and draw heat maps, and the similarity comparison between the generated patterns with three different structures and the original samples is shown in Figures 7, 8 and 9. The right side of the figure shows the similarity threshold color bar, in order to facilitate the distinction, from 0-1.00 each number corresponds to a color, 0 is similarity of 0, 1.00 is similarity of 100%; the threshold color bar value has no unit.

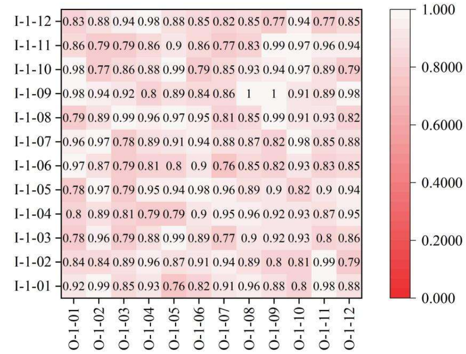

Figure 7: Comparison of the similarity between the generated Image 1 and the sample

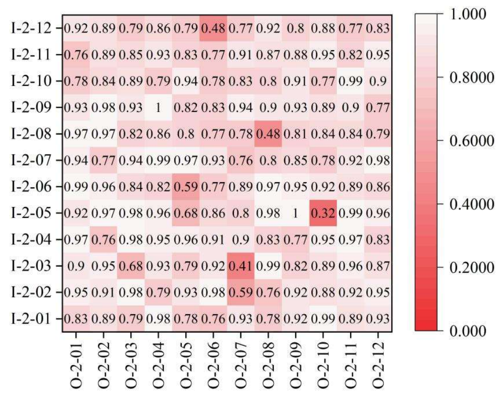

Figure 8: Comparison of the similarity between the generated Image 2 and the sample

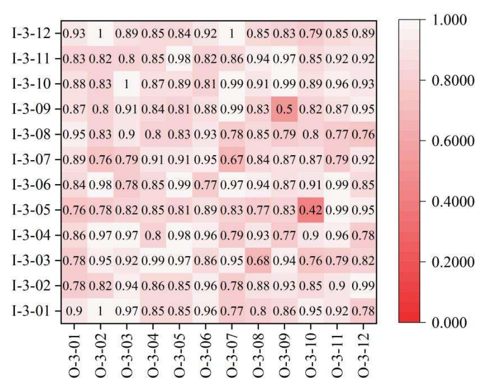

Figure 9: Comparison of the similarity between the generated Image 3 and the sample

The percentages of image pairs with similarity thresholds above 0.85 between the three types of structure-generated patterns and the original samples are 96.29%, 86.27% and 90.88%, respectively. It can be seen that the model trained in this paper basically conforms to the morphology and structure of decorative tattoos of the Central Plains culture.

III. D. 3) Qualitative analysis

The qualitative analysis aims to gain an in-depth understanding of the artistic characteristics and visual effects of the generated images. In this paper, we get the evaluation of the appearance characteristics of the tattoos from the styling index (S) and the color index (C), the evaluation of the intrinsic performance of the tattoos from the aesthetics index (A) and the innovation index (Cr), and the evaluation of the value of the tattoos' application from the application index (P), and the comprehensive score according to the weights is used as the basis of the qualitative analysis. The weights of the five indicators are [0.174,0.187,0.204,0.172,0.263].

The questionnaire survey randomly selected 15 groups of experimentally generated tattoos respectively from the tattoo appearance characteristics, tattoo inner performance and tattoo practical value evaluation of three dimensions to seek evidence of the design evaluation of tattoo images. In this paper, the research was conducted in the form of online questionnaire, the total number of questions was 12, and 175 valid feedbacks were received, and the research objects accounted for about 61.14% of the art and design related personnel, and 38.86% of the other personnel.

The questionnaire randomly selects 15 groups from a database of 100 tattoos with an average number of occurrences per group of 25. Respondents are required to score and evaluate the 15 groups of tattoos grouped together and each group contains three tattoos that are tattoo images corresponding to the same descriptive text, which are the original tattoos, the original tattoos, this paper's fusion of traditional tattoo gene networks with multi-objective evolutionary computation MOEAs based on the Cycle GAN network for idea generative framework to generate tattoos, and traditional AI tentacles to generate tattoos. Respondents scored each group of tattoos on each of the 8 questions from 3 dimensions. The ratings are categorized into five levels based on the “Likert five-point scale”, where “1” represents negative absolute negativity and “5” represents positive absolute affirmation of the results. Table 3 shows the evaluation scores of respondents in different occupations.

Table 3: Evaluation scores of respondents from different occupations

Generation method	Interviewee	Score category	Pattern appearance characteristics		The internal expression of the pattern		Practical value of patterns	Comprehensive score
			Modeling features (S)	Color characteristics (C)	The aesthetic appeal of the generated patterns (A)	The degree of innovation in generating patterns (Cr)	The application of generating patterns (P)	
OURS	Art personnel	Original	3.05	2.94	2.70	2.98	3.52	3.04
		Weight	0.531	0.550	0.551	0.513	0.926	3.07
	Other personnel	Original	4.55	4.29	3.85	4.45	3.73	4.17
		Weight	0.792	0.802	0.785	0.765	0.981	4.13
Traditional AI tentacles	Art personnel	Original	2.37	1.97	2.08	2.74	1.95	2.22
		Weight	0.412	0.368	0.424	0.471	0.513	2.19
	Other personnel	Original	3.43	3.72	3.82	3.98	3.33	3.66
		Weight	0.597	0.696	0.779	0.685	0.876	3.63

Table 3 demonstrates the results of the subjective evaluation of the generative model proposed in this paper and the traditional AI-generated tattoos by respondents from different professions. Among the art design practitioners, the raw scores of the OURS model on stylistic index (S), color characteristics (C), aesthetic appeal (A), degree of innovation (Cr) and application value (P) are 3.05, 2.94, 2.70, 2.98 and 3.52, respectively, with a composite score of 3.04, and a weighted score of 3.07; whereas, the corresponding scores of traditional AI-generated tattoos is significantly lower, S=2.37, C=1.97, A=2.08, Cr=2.74, P=1.95, and the composite score is only 2.22. It is worth noting that the art designers rate the color characteristics of the tattoo images generated by the model of this paper at 2.94, as well as 2.98 on the degree of innovation, which is a relatively conservative evaluation, but the application value of P=3.52 is recognized more highly, and the The weighting analysis shows that the weight of application value is 0.263, which contributes the most to the composite score.

Respondents from other professions generally rated the tattoo images generated by this paper's model higher, with a composite score of 4.17, especially in the modeling features S=4.55 and color features C=4.29, and the degree of innovation Cr=4.45 and the application value P=3.73 are both better than the composite score of the traditional AI-generated tattoos, which is 3.63. Cross-sectional comparisons show that regardless of the occupational backgrounds, the model of this paper, which integrates the evolutionary computation and AICG methods, is significantly better than the traditional methods in all indicators, especially in the field of art and design. Evolutionary computation and AICG methods in this paper is significantly better than the traditional method in all indicators, especially in the field of art and design is more recognized, indicating that its generation of tattoos is more advantageous in terms of professionalism and practicality.

Continue to do a specific analysis of the pattern image generated by the model. Tattoo images have been widely used in various fields of art and design, different design fields on the pattern of the pattern of the form, color, pattern demand is different, this paper according to the needs of art design will be divided into the pattern of simple abstract pattern, complex figurative type, monochrome, color, separate and multiple integrated pattern, a total of six categories. The experiments use the generative design method of this paper to experimentally verify the 6 categories of tattoos, which are 48 simple abstract samples, 47 complex figurative samples, 50 monochrome samples, 40 color samples, 60 individual tattoos, and 30 multivariate integrated tattoos, respectively.

This section compares this paper's model in terms of the generation of the above six types of tattoo samples. The model in this paper has a high degree of matching in the generation of geometrized lines and basic pattern elements, and can continue the style of the original pattern with rich variations when generating monochrome patterns. When generating color patterns, it can maintain high hue consistency and restore complex colors. In the generation of individual patterns and multiple integrated patterns, the model also shows potential, with flexibility and harmony. The model in this paper is also good at visual innovation, especially in generating figurative patterns, presenting new forms and compositions, with a more complete and unified composition form.

Figure 10 shows the subjective evaluation scores of the six categories generated by this paper's method regarding the generation of tattoo images from the Central Plains culture.

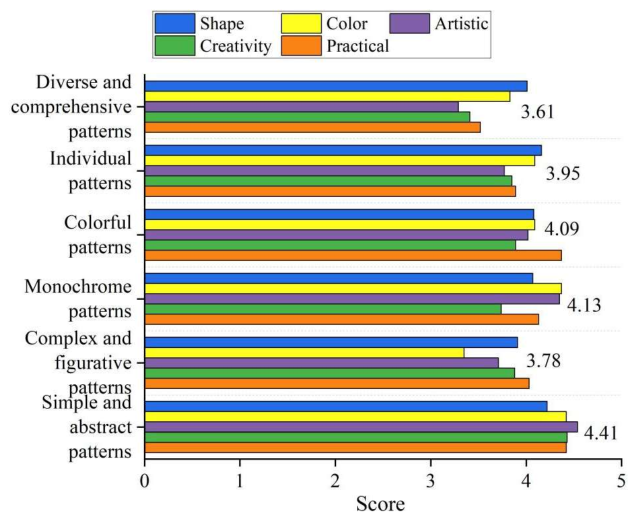

Figure 10: Subjective evaluation score of the six major categories of generated patterns

The generation effects of the six types of Central Plains cultural patterns were compared from a subjective evaluation perspective. The simple and abstract type pattern performed the best, with a composite score of 4.41, in which the aesthetic appeal A=4.54 and the degree of innovation Cr=4.42 were particularly outstanding, indicating that the model has a high degree of matching and flexibility in the generation of geometric lines and basic patterns. Complex figurative patterns had the lowest overall score of 3.78, with a relatively weak degree of innovation Cr=3.35 and application value P=3.91, probably stemming from the high difficulty in generating details for complex structures. Monochrome tattoos 4.13 and color tattoos 4.09 had similar scores, but the degree of innovation of monochrome tattoos Cr=4.37 was significantly higher than that of color tattoos Cr=4.09, suggesting that the model was more advantageous in monochrome style continuation, while color tattoos were slightly weaker in color consistency C=3.89. The score difference between 3.95 for single pattern and 3.61 for multiple integrated pattern reflects the model's stability in single composition is better than that of complex combination design, but the higher application value of P=4.01 for multiple integrated pattern indicates that it still has the potential in practical scenes. Overall, the model performs best in simple abstraction, monochrome and individual pattern generation, verifying its effectiveness in style continuation and integration of basic design elements.

IV. Conclusion

In this study, we constructed a CycleGAN-based Central Plains cultural pattern generation model by integrating traditional pattern gene network and multi-objective evolutionary computation MOEAs, which realizes the accurate migration and innovative expression of traditional styles. On the PASCAL VOC 2020 dataset, the model pattern segmentation accuracy MIoU=86.67%, which is 3.21 percentage points higher than the mainstream model, and the FID value of the generated image is 6.83 and the IS value is 5.34 verifying its high quality and diversity. On the self-constructed ZYWY dataset, the cosine similarity threshold between the generated tattoos and the original samples is higher than 0.85 in more than 90% of the cases, which indicates that the model can effectively retain the core features of the Central Plains cultural tattoos. The ablation experiment further reveals the critical impact of the 8.46% decrease in MIoU of the traditional tattoo gene network and the 9.2% decrease in IS of the channel attention mechanism on the generation effect. In the subjective evaluation, the simple abstract tattoo had the highest composite score (4.41), while the complex figurative tattoo (3.78) was slightly weaker due to the higher difficulty of detail generation, but the application value (P=3.91) still has potential. The study shows that the model has significant advantages in the continuation of pattern style, diversity generation and adaptability to practical application scenarios, which provides a new technical path for the digital protection and innovative design of cultural heritage.

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