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Geometric Morphology Optimization Method Based on Image Recognition Technology in Lacquerware Pattern Designs

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Abstract As a traditional Chinese handicraft, the pattern design of lacquer ware has important cultural value and artistic charm. Traditional lacquerware pattern design mainly relies on manual production, which has problems such as low efficiency and poor precision. The development of modern computer vision technology provides new ideas for the automatic identification and optimization of lacquerware patterns. It is of great significance to inherit and develop lacquer art by realizing automatic detection and classification of lacquer patterns through image recognition technology, and optimizing and innovating the geometric form of the patterns by combining with intelligent algorithms. Objective: Aiming at the problems of low efficiency and lack of innovation in traditional lacquerware pattern design, this study proposes a method of optimizing the geometric form of lacquerware patterns based on image recognition technology to realize automatic detection, classification and innovative design of lacquerware patterns. Methods: Improved Canny algorithm is used for lacquerware pattern contour detection, and the detection accuracy is improved by bilateral filtering, multi-directional Sobel template and interactive threshold detection based on Otsu, etc.; HOG feature extraction and SVM classifier are used to realize automatic detection of lacquerware patterns; optimization and innovation of the geometric form of the lacquerware patterns are carried out based on BP-GA algorithm; and virtual reality technology is used to carry out the Perceptual imagery evaluation experiment. Results: The experimental results show that the lacquerware pattern detection model proposed in this paper achieves 94.80% mAP in the recognition of 7 pattern types, among which the best effect is achieved in the detection of plant patterns, with 96.09% mAP among classes; in the pattern classification task, the accuracy of the model in this paper reaches 94.73%, with 94.14% F1 score; the optimized lacquerware patterns are more effective in the recognition of the sensual imagery in the categories of "hip" and "chic"; and the optimized lacquerware patterns are more effective in the recognition of the sensual imagery in the categories of "new" and "chic". Conclusion: The method in this paper effectively improves the recognition accuracy and classification performance of lacquerware patterns, and the optimized pattern geometry of the BP-GA algorithm is more in line with the modern aesthetic demand, which provides technical support for the digital protection and innovative development of traditional lacquerware art.

Index Terms Lacquerware pattern, Image recognition, Geometric form optimization, HOG features, BP-GA algorithm, Perceptual imagery evaluation

I. Introduction

Lacquerware art is an ancient and precious art form which has a long tradition in Chinese history. Lacquerware is widely recognized as one of the most representative crafts of Chinese cultural heritage, which not only demonstrates the aesthetic interest of Chinese culture, but also is the embodiment of the high level of craftsmanship in ancient China [1], [2]. The art of lacquerware is famous not only for its superb artistic creation skills, but also for its practicality for people's use [3]. In ancient times, lacquerware was widely used in the court, which is closely related to its position in Chinese culture and history [4]. The Chinese regarded lacquerware as a representative of traditional fashion and heavy culture, and it became a preferred item for the aristocracy and the court because of its unique protection and durability against corrosion, fire, water, and insects [5], [6].

Pattern design in lacquerware craft products is different from painting design in general craft products, which not only requires a certain degree of artistic cultivation, modeling ability and life foundation, but more importantly, mastering the special characteristics of lacquerware craft and the special language of lacquer art, understanding the nature of lacquer, being familiar with the means of craftsmanship, and making it organic, in order to better and freely utilize and bring into play the artistry of lacquerware craft [7]-[10]. However, lacquerware pattern design is difficult to cope with the current consumer demand due to the long cycle of pattern drawing, low design efficiency, low precision of geometric forms, and distortion of the replica of the pattern craft, and the effect of pattern innovation and design [11], [12]. Among them, geometric form is the product of figurative graphics being symbolized and refined, due to its neat construction, bright lines, simple shape can contain rich connotations and the era of the Chinese aesthetic interest, and thus has a long history of use, is the main symbol of the design from tradition to modernity, and runs through the whole of the modern design [13], [14]. Therefore, it is necessary to optimize the geometric forms in the design to help the innovation of lacquer pattern design. With the arrival of the digital era, image recognition technology has become an integral part of the field of computer vision. It processes and analyzes images through computers in order to identify target objects or features in the images, and this technology plays an important role in the design field, such as product development [15]. In the design field, image recognition technology is utilized to extract features from patterns, obtain pattern accuracy, and generate new patterns, which not only shortens the design cycle, but also provides accurate retention of patterned cultural symbols [16].

Lacquerware, as an outstanding representative of Chinese traditional crafts, carries deep cultural connotation and unique artistic value in its exquisite pattern design. Traditional lacquerware pattern creation mainly relies on craftsmen's manual skills and experience accumulation, and although this approach can reflect individualization and artistry, there are obvious limitations in terms of efficiency, precision and innovation. Under the background of rapid development of contemporary digital technology, how to combine modern computer vision technology with traditional lacquer art to realize intelligent recognition and innovative design of lacquer patterns has become an important topic in the field of cultural heritage protection and inheritance. Image recognition technology, by simulating the human visual system, can automatically extract and analyze the feature information in images, and has achieved remarkable results in the fields of target detection and pattern recognition. Applying this technology to the recognition and analysis of lacquerware patterns can not only improve the efficiency and accuracy of pattern processing, but also provide technical support for the digital archiving and inheritance of patterns. Meanwhile, the optimization algorithm based on artificial intelligence can explore new design possibilities on the basis of preserving the essence of traditional patterns and realize the organic integration of tradition and modernity.

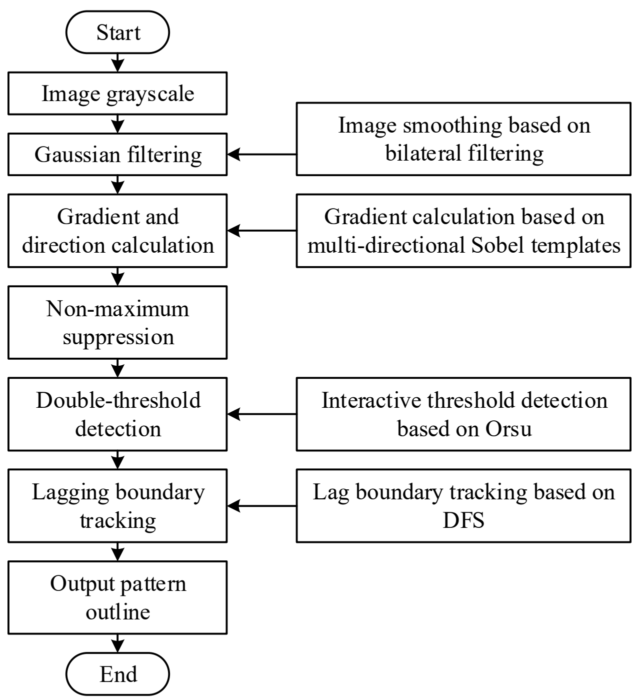

Figure 1: Pattern outline detection based on improved Canny algorithm

This study starts from the two dimensions of automatic recognition and innovative design of lacquerware patterns, firstly, a pattern contour detection framework based on the improved Canny algorithm is constructed to improve the accuracy of pattern feature extraction by optimizing the traditional edge detection method; secondly, a pattern recognition model is established by adopting HOG features combined with SVM classifiers to realize the automatic classification of multiple types of lacquerware patterns; on the basis of which, a BP neural network and genetic algorithm combined optimization strategy to carry out innovative design of the geometric form of lacquerware patterns; finally, the perceptual imagery evaluation experiment is carried out through virtual reality technology to verify the effectiveness of the optimization scheme and user acceptance. The whole research process forms a complete technical system from pattern recognition to innovative design to effect evaluation, providing a new technical path for the digital development of lacquer art.

II. Lacquerware pattern detection based on image recognition

II. A. Lacquerware pattern contour detection based on improved Canny algorithm

In this paper, the improved Canny algorithm is used for lacquer pattern contour detection as shown in Fig. 1, where the right box indicates the improved part, bilateral filtering is used instead of Gaussian filtering in order to obtain a smooth image of the fabric pattern, the improved Sobel gradient template is used to obtain the gradient matrix, and the design of Otsu-based interactive threshold detection and DFS-based hysteresis boundary tracking is used to optimize the effect of the detection of the fabric pattern contour.

II. A. 1) Lacquer pattern image grayscaling

In order to reduce the amount of raw data processing, it is first necessary to convert color images into grayscale images. For the grayscale of color lacquer pattern images, there are three methods as follows:

1) Mean value method. Calculate the average value of the R, G and B components for each pixel point in the color RGB image to find the grayscale value of the corresponding pixel point, as in equation (1):

$$f(i,j)=\frac{1}{3}(R(i,j)+G(i,j)+B(i,j)) \tag{1}$$

2) Maximum value method. The maximum value in the R, G, and B components of a pixel point in a color RGB image is taken as the gray value of the corresponding pixel point, as in equation (2):

$$f(i,j)=\max(R(i,j),G(i,j),B(i,j)) \tag{2}$$

3) Weighted average method. According to the degree of importance or theoretical criteria, different weighting coefficients are set to take the weighted average of the three R, G and B components of each pixel point in the color RGB image, which is used as the grayscale value of the corresponding pixel point.

Considering the physiological structure of the human eye, which is sensitive to green light and less sensitive to red and blue light, the following formula (3) is used for the weighted average graying calculation of lacquer pattern images:

$$f(i,j)=0.299*R(i,j)+0.578*G(i,j)+0.114*B(i,j) \tag{3}$$

The original image of the lacquer pattern is weighted average grayscaled to obtain a reasonable grayscaled image that conforms to the visual effect of the human eye, which can be used as the input image for subsequent smoothing filtering.

II. A. 2) Image smoothing based on bilateral filtering

The bilateral filter uses two Gaussian functions characterizing the spatial distance and the gray distance [17]. The Gaussian function characterizing the spatial distance is shown in equation (4):

$$G_{\sigma_s}(\| p-q \|)=e^{\frac{(x_p-x_q)^2+(y_p-y_q)^2}{2\sigma_s^2}} \tag{4}$$

where (x_p, y_p) is the position of a point p in the neighborhood, (x_c, y_c) are the coordinates of the centroid q, and σ_s is the standard deviation of the Gaussian function characterizing the spatial distance. The Gaussian function characterizing the gray distance is shown in equation (5):

$$G_{\sigma_r}(| I_p - I_q |)=e^{\frac{(gray(x_p,y_p)-gra(x_q,y_q))^2}{2\sigma r^2}} \tag{5}$$

where $gray(x_p, y_p)$ is the gray value of a point p in the neighborhood, $gray(x_q, y_q)$ is the gray value of the center point q, and σ_r is the standard deviation of the Gaussian function characterizing the gray distance. It is obtained from Eqs. (4) and (5):

$$BF[I]_p=\frac{1}{W_P}\sum_{q\in S}G_{\sigma_s}(\| p-q \|)G_{\sigma_r}(| I_p - I_q |)I_q \tag{6}$$

$$W_P=\sum_{q\in S}G_{\sigma_s}(\| p-q \|)G_{\sigma_r}(| I_p - I_q |)I_q \tag{7}$$

Eq. (6) is the final bilateral filter operator template and Eq. (7) is the bilateral filter operator normalization coefficients.

II. A. 3) Gradient computation based on multidirectional Sobel templates

After the lacquer pattern image is filtered, in order to locate the regions in the image that may be edges, the Canny detection algorithm generally uses the Sobel gradient template to calculate the gradient and the direction angle at each location in the image [18]. The Sobel gradient templates for the horizontal and vertical directions are shown in Eqs. (8) and (9):

$$s_x = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \tag{8}$$

$$s_y = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} \tag{9}$$

where Eq. (8) is the gradient template in the x-direction of the Sobel operator and Eq. (9) is the gradient template in the y-direction of the Sobel operator.

II. A. 4) Non-extreme value suppression

After the above steps to derive the gradient matrix of the lacquer pattern image, the large value of an element in the matrix does not guarantee that the corresponding pixel point must be an edge point. Therefore, the gradient image must be subjected to non-extremely large value suppression [19], the principle of which is shown in Fig. 2. C represents the center point, $g1$、$g2$、$g3$、$g4$ represents the four neighboring points of the center point C, and the red line characterizes the gradient direction of the center point C. To perform non-maximal value suppression for the point C, the gradient value of C is first compared with the gradient values of $Temp1$ and $Temp2$ so it is necessary to interpolate the gradient values of $Temp1$ and $Temp2$ gradient values of the two points. First, the gradient value at $g1$、$g2$ is interpolated to obtain the gradient value at $Temp1$, and the gradient value at $Temp2$ is interpolated to obtain the gradient value at $g3$、$g4$, and then, the gradient value at the center point C is compared to the gradient values at $Temp1$ and $Temp2$, respectively, and if the gradient values at the center point C are both greater than the values of the gradients at $Temp1$ and $Temp2$, the center point C is retained, if the gradient value at the center point C is less than the gradient value at either $Temp1$ or $Temp2$ the center point C is suppressed and the gray value of the center point C is set to zero.

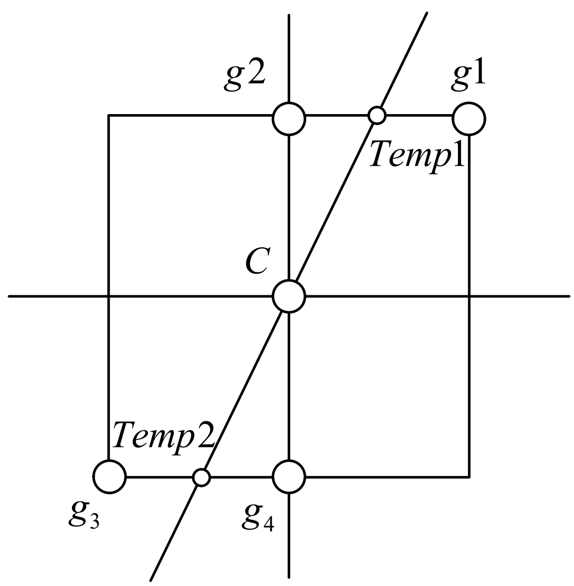

Figure 2: Non-maximum suppression principle

The gradient image of the lacquer pattern image is suppressed by non-extremely large value, and after the non-extremely large value suppression, some non-extremely large pixel points in the gradient calculation map of the lacquer pattern are removed from the image, which initially presents the general outline of the lacquer pattern.

II. A. 5) Otsu-based Interactive Threshold Detection

After the non-extremely large value suppression, there may still exist a lot of non-edge points in the lacquer pattern image, and it is necessary to use double threshold detection to further screen the edge points.The Canny detection algorithm does not give a suitable method to determine the size of the threshold, and it is generally necessary to set it manually according to experience, but this way will reduce the efficiency of the algorithm to some extent. To address this problem, Otsu segmentation [20] is first applied to the gray-scale image, whose threshold is used as the Canny high threshold reference value, and half of the high threshold is used as the Canny low threshold reference value, and then the interaction module is established through the createTrackbar() and callback function, which facilitates the operator to adjust the threshold detection effect of the image, so as to determine the optimal detection threshold value.

II. A. 6) DFS-based lag boundary tracking

Since the Canny high threshold is generally set high in the above steps, which easily leads to the existence of edge discontinuities in the reconstructed lacquerware pattern contour image, it is necessary to repair the discontinuous edges by lagged boundary tracking, and at the same time, the DFS method is able to find all the boundary connectivity schemes in the lacquerware pattern image as much as possible, and it occupies less memory. Therefore, DFS based lagged boundary tracking technique is used to repair the lacquerware pattern detection edges. The lacquer pattern lagged boundary tracking image is corrected for the lacquer pattern threshold detection image edge details and is output as the final detection result.

II. B.Lacquer pattern detection based on HOG+SVM

II. B. 1) Extracting HOG features of lacquer patterns

The specific steps for the implementation of HOG features are as follows:

Step 1: Image standardization.

Mainly also includes image segmentation image grayscale and other preprocessing. The specific formula is:

$$I(x,y)=I(x,y)^{gamma} \tag{10}$$

where $I(x,y)$ denotes the position of each pixel in the image.

Step 2: Gradient calculation.

After clarifying the module division in HOG feature extraction then the gradient calculation needs to be performed. The gradient calculation of an image includes gradient magnitude calculation and gradient direction calculation. The magnitude of the gradient is related to the size of the gradient, the larger the magnitude of the gradient, the larger the weights in the corresponding direction. The calculation of the magnitude also includes the gradient magnitude in the horizontal direction and the gradient magnitude in the vertical direction. After the calculation of the magnitude value, the gradient direction value for each pixel position needs to be calculated based on the magnitude value.

According to the gradient operator in both directions, we need to calculate the gradient at pixel (x,y) at the position (x,y) of the image. $I(x,y)$ denotes the pixel value at pixel point (x,y), the horizontal direction gradient magnitude is calculated as the difference between neighboring pixels $G_x(x,y)$, and the vertical direction gradient magnitude is calculated as the difference between the upper and lower pixels $G_y(x,y)$ Calculation formulae are respectively:

$$G_x(x,y)=I(x+1,y)-I(x,y) \tag{11}$$

$$G_y(x,y)=I(x,y+1)-I(x,y) \tag{12}$$

The gradient magnitude $G(x,y)$ and gradient direction $\alpha(x,y)$ at the pixel point $I(x,y)$ after calculation of the horizontal and vertical direction operators, respectively:

$$G(x,y)=\sqrt{G_x(x,y)^2+G_y(x,y)^2} \tag{13}$$

$$\alpha(x,y)=\tan^{-1}\left(\frac{G_y(x,y)}{G_x(x,y)}\right) \tag{14}$$

Step 3: Divide the image into 460 Cells.

In lacquer pattern feature extraction in this paper, each image is divided into 460 Cells, and then construct the gradient direction histogram for each Cell. The gradient histogram includes direction and magnitude, and the direction of the gradient direction histogram can usually be divided into 9 histogram channel directions.

Step 4: Region crosstalk.

Combine cell units Cell into large Block regions, 460 Cell units can be combined into 115 Block regions. Then normalize the gradient histogram within each Block region, every four Cell cells can be combined into one Block region, and there are 9 Bin features in each Cell cell. We finally concatenate the Bin's features in all Cell cells into regions, and we can get the features of each Block.

Step 5: Collect HOG features for threshold judgment.

After the previous HOG feature extraction, we can collect the HOG features, and then use the relevant algorithms of machine learning to make the threshold judgment.

II. B. 2) Optimization of HOG feature extraction algorithm

In the general HOG algorithm the projected Bin angle is projected based on the calculated $\alpha(x,y)$ value, but this value is not necessarily fixed to a certain Bin taken in the middle. So we optimize the gradient angle projection to get the following magnitude formula:

$$G(x,y)_1 = G(x,y) \times P_{\alpha(x,y)} \tag{15}$$

$$G(x,y)_2 = G(x,y) \times (1 - P_{\alpha(x,y)}) \tag{16}$$

where $G(x,y)$ denotes the magnitude at pixel point $I(x,y)$, and $P_\alpha(x,y)$ denotes the probability that the angle is occupied at Bin plus 1. After the above optimization we decompose the original magnitude to get two magnitudes $G(x,y)_1$ and $G(x,y)_2$, and then we multiply the weights and Cells for all the magnitudes.

II. B. 3) HOG+SVM based image detection

The HOG features of the lacquer pattern are extracted using the improved HOG feature extraction algorithm [21], and then the SVM algorithm is used to train the lacquer pattern to achieve the detection of the lacquer pattern.

Step 1: Prepare the sample. The lacquer pattern is preprocessed in the previous section, and then the processed lacquer pattern is divided into positive and negative samples. The target pattern to be detected is included in the positive sample, and the lacquerware pattern to be detected cannot appear in the negative sample.

Step 2: HOG+SVM training. The process of HOG+SVM training in this paper is shown in Figure 3.

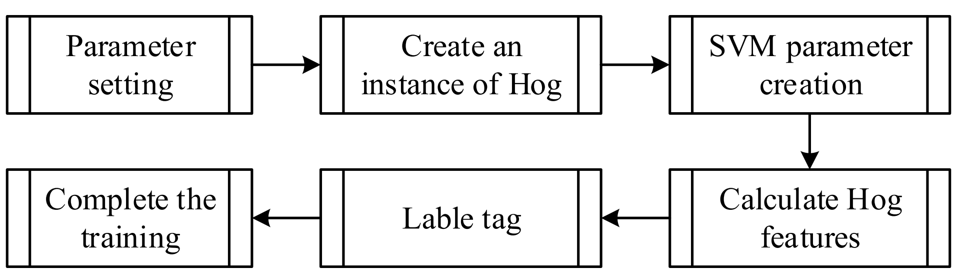

Figure 3: HOG+SVM training process

Step 3: Lacquerware pattern detection. After completing the training of HOG+SVM samples, the final step is to detect the lacquer pattern in the input test image.

III. Innovative Design of Lacquerware Pattern Geometry Based on BP-GA

Genetic algorithms simulate the natural evolutionary laws of the biological world, starting from an initial population, and generating a group of new individuals through random crossover, mutation, replication and other operations. In the new individuals will be able to adapt to the environment will be retained, used to expand the search space in the process of population evolution, with the increase in the number of generations of population evolution, the final best adapted to the environment of a group of individuals will be retained, as the optimal solution to the problem. The basic flow of the genetic algorithm is shown in Figure 4.

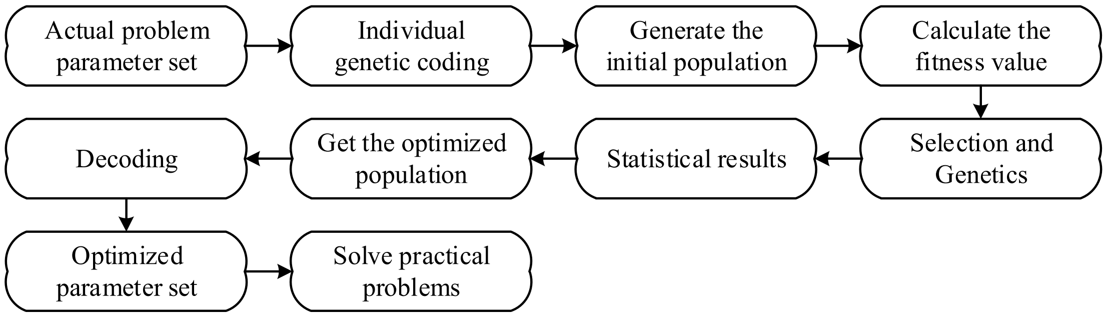

Figure 4: Basic process of genetic algorithm

(1) Coding of geometric morphology element genes

Coding is the first problem to be solved in genetic algorithms, and the success or failure of coding will directly affect the subsequent genetic operations such as selection, crossover and mutation. Usually there are binary coding, Gray code coding, real number coding and so on. The geometric morphological features of the lacquer pattern are divided into elements, and each element can be regarded as a gene in the genetic algorithm. Combined with the BP network user satisfaction prediction model, real number coding is used to genetically encode each lacquerware pattern geometric form element.

(2) Individual chromosome coding of the initial population

The geometric form elements (genes) of each sample are connected head to tail and constitute a chromosome of lacquerware pattern, which corresponds to a lacquerware pattern geometric form scheme.

(3) The fitness function is also a function that evaluates how good or bad an individual is in the genetic process, and is the only basis for natural selection, which is expected to be as large as possible in any case. The fitness function of the genetic algorithm is shown in equation (17). Select the allocation function ranking in the genetic algorithm toolbox:

$$Y = f(\sum_{i=1}^{m} w_i K_i) + b \tag{17}$$

Among them, $K_i = f(\sum_{j=1}^{9} v_{ji} L_i) + b_i = \frac{1}{1+e^{-\sum_{j=1}^{n} v_{ji} L_i}} + b_i \quad i = 1, 2, \cdots, m \quad (m = 6)$.

Among them, Y is the output layer value (i.e., the user satisfaction value), and L_i is the input layer value (the geometric shape feature value of the modeling part). BP network training f function is used when the transfer function, v_{ji} is the first j a input layer nodes and hidden layer between the first i of a node weights, w_i is the first i a hidden layer node weights between hidden and output layer, b_i is the threshold of the i th node in the hidden layer, and b is the threshold of the output layer.

(4) Genetic algorithm related parameter settings

In the optimization process of genetic algorithm, there are mainly basic operations such as selection, crossover and mutation. When carrying out genetic algorithm calculations, some basic parameters need to be selected beforehand, including the size of the initial population, crossover rate, mutation rate and so on.

1) Selection: Select the individual with better genes in the population as the parent for the next generation. In this paper, select function is chosen to call the function sus for individual selection.

2) crossover: the purpose is to produce new individuals, in this genetic algorithm program using advanced recombination function recombbin call multipoint crossover function xovmp to achieve the gene crossover operation, the crossover rate is generally selected larger, but not too large, generally take 0.5 to 0.9.

3) Variation: variation is to be able to get more populations and expand the population range. This genetic algorithm optimization system of mutation operation using the function mutate call real-valued mutation function mutbaga. Generally take 0.001 ~ 0.1.

4) Genetic termination criterion: in order to get more excellent individuals in the process of evolution, try to take a larger number of evolutionary generations, but generally depending on the specific problem, take 100 to 1000 generations.

IV. Pattern form optimization effect analysis

IV. A. Image recognition effect analysis

IV. A. 1) Pattern recognition

In order to understand the image recognition and classification effect of the lacquer pattern detection method in this paper, experiments are carried out according to the network model constructed in the paper, which is trained separately. The experiments used for the homemade dataset, which contains 4000 image data of seven lacquerware patterns, in the pattern annotation, in order to realize the simultaneous recognition of multiple patterns, deliberately choose each image data contains a variety of patterns for annotation. The main form of data embodiment is to contain one or more patterns of the corresponding category, and one or more patterns of different categories, so there are more than three thousand pattern data in the model experiment. The experiment is a comparison experiment of three target detection models with the same parameter settings. The training set and test set are set to 8:2 for the experiment, and after training, the lacquer pattern target detection results are obtained as shown in Table 1.

Comparing the results of the following three models, when the confidence score threshold is set to 0.65, it is the model of this paper that shows better performance in recognizing and localizing the patterns, with a detection mAP of 94.80%. Among the three main classes of patterns, the best detection is the plant class pattern with an inter-class mAP of 96.09%, and the worse detection is the animal class pattern with an inter-class mAP of 93.33%. The detection effect of texture class patterns is in the middle with a mAP of 94.98%.

By comparing the magnitude of the values of check accuracy and recall of the three models in Table 1, it is found that using the detection model constructed in this paper yields the highest check accuracy and recall, so the model can detect more correct lacquerware patterns. More number of patterns can be detected. Different detection models can be selected in subsequent research and applications according to the focus of lacquerware pattern detection. If the number of correctly detected patterns and the overall number of detections need to be balanced, the F1 index can be compared to select the detection model. The F1 value of the model in this paper is clearly better than using YOLOv3 and Faster R-CNN model.

Table 1: Lacquer pattern recognition results

Model	Lacquer pattern type		F1	Recall/%	Accuracy/%	Average accuracy/%	Interclass mAP/%	mAp/%
YOLOv3	Texture	Lattice & streak	0.69	74.51	82.48	84.26	84.69	84.00
		Wave point	0.71	76.76	82.54	85.12		
	Plants	Flower & grass	0.85	66.14	81.15	80.47	82.72	
		Trees	0.82	61.29	85.18	84.96		
	Animals	Cats	0.82	81.94	80.24	82.74	84.58	
		Dogs	0.85	84.97	84.96	86.42		
Faster R-CNN	Texture	Lattice & streak	0.74	84.88	86.95	84.29	84.23	74.94
		Wave point	0.75	82.26	82.71	84.17		
	Plants	Flower & grass	0.85	55.48	79.36	76.94	76.59	
		Trees	0.86	59.16	74.89	76.23		
	Animals	Cats	0.73	84.75	61.39	64.05	64.00	
		Dogs	0.74	88.47	61.07	63.94		
Ours	Texture	Lattice & streak	0.92	90.25	96.63	97.09	94.98	94.80
		Wave point	0.93	91.88	90.33	92.86		
	Plants	Flower & grass	0.89	90.09	95.52	96.34	96.09	
		Trees	0.91	85.56	93.45	95.84		
	Animals	Cats	0.93	92.53	91.42	92.37	93.33	
		Dogs	0.93	94.28	93.35	94.29		

IV. A. 2) Pattern classification

In this subsection, five different network architectures (i.e., Inception-v3, GoogLeNet, VGG16, ResNet50, and EfficientNet-B0) are selected and applied to the training of lacquerware image dataset. By relocating the data enhancement technique, the corresponding five models are generated: DTL-Inception-v3, DTL-GoogLeNet, DTLVGG16, DTL-ResNet50, and DTL-EfficientNet-B0. Each model is trained by five-fold cross-validation, and then an independent test is conducted to combine the above models with the models in this paper Tests were conducted and the detailed performance of the test set is shown in Table 2, where these improved models outperform the traditional models in terms of performance. The introduction of data enhancement does improve the classification results. For example, DTL-EfficientNet-B0 improves 5.73% and 7.93% in terms of accuracy and F1 score, respectively, compared to the traditional EfficientNet-B0. However, compared with the model in this paper, the other models still have a large gap in precision, recall, F1 and accuracy. The model in this paper achieves the best performance with 94.44%, 96.02%, 94.14%, and 94.73% for precision, recall, F1, and accuracy, respectively. In addition, the overfitting problem of the model is effectively mitigated.

Table 2: Classification performance comparison

Model	Precision	Recall	F1-score	Accuracy
VGG16	0.8726	0.8665	0.8539	0.8856
DTL-VGG16	0.8935	0.9289	0.9016	0.9294
Inception-v3	0.8174	0.8213	0.8251	0.8756
DTL-Inception-v3	0.8714	0.9026	0.9195	0.9081
GoogLeNet	0.7332	0.7946	0.7804	0.7966
DTL-GoogLeNet	0.8437	0.8607	0.9166	0.8923
Resnet50	0.7827	0.8425	0.8276	0.8231
DTL-Resnet50	0.8633	0.9187	0.8958	0.8859
Efficionnet-B0	0.8231	0.8235	0.8013	0.8379
DTL-Efficionnet-B0	0.8843	0.8989	0.8806	0.8952
Ours	0.9444	0.9602	0.9414	0.9473

IV. B. Evaluation of perceptual imagery

After optimizing and innovating the geometric form of lacquerware patterns based on the BP-GA algorithm, virtual reality (VR) simulation experiments were conducted to evaluate the optimization scheme. The finished creation was shown in VR to 150 survey respondents, and the subjective feelings of the survey respondents on the finished lacquerware pattern forms were collected to constitute a perceptual imagery evaluation of them.

IV. B. 1) Perceptual Imagery Evaluation Scale

Based on 10 original lacquerware representative samples and 4 representative perceptual imagery vocabularies, a questionnaire was designed for perceptual imagery experiments to establish a scale for evaluating perceptual imagery of the geometric forms of lacquerware patterns. Subjects were required to evaluate 10 representative samples (numbered S1~S10) based on the 4 representative perceptual vocabulary words, and scored on a 7-point Likert scale, where level 1 indicates the least obvious feeling and level 7 indicates the strongest feeling. Results 142 valid questionnaires were recovered, and the data were counted, mean values were calculated and summarized, and the results are shown in Table 3.

From the results of Table 3, the participants' subjective feelings towards the geometric forms of the patterns on the 10 selected lacquerware samples were rated as "traditional" and "solemn", with mean scores of 4.12 and 3.94 respectively. In contrast, the mean scores for "trendy" and "distinctive" were 3.67 and 3.90 respectively. This subjective evaluation aligns with the public's consistent perception and impression of lacquerware.

Table 3: Perceptual image evaluation scale

Sample	Average evaluation score			
	Traditional	Solemn	Trendy	Special
S1	4.03	4.06	4.04	4.02
S2	3.97	3.78	3.94	3.93
S3	4.24	3.83	3.43	3.75
S4	4.04	4.11	3.33	3.92
S5	4.24	3.68	3.54	3.93
S6	3.89	3.77	4.07	3.79
S7	4.31	4.04	3.94	3.85
S8	4.02	4.13	3.06	3.92
S9	4.25	4.23	4.08	4.02
S10	4.22	3.72	3.27	3.84

IV. B. 2) Simulation experiment results

The 10 lacquerware samples in Section 4.2.1 are optimized by the BP-GA algorithm in this paper and demonstrated using VR technology.VR technology can accurately simulate and display complex design solutions and environments in 3D form, which can make up for the lack of the user's experience in terms of spatial layout, dimensional proportions, and lighting effects when observing 2D pictures. In addition, using VR technology for program evaluation can significantly reduce the production cost and time of physical prototypes, allowing multiple iterations and modifications of the design at a lower cost. The subjective evaluations of the optimized lacquerware samples were again collected from the subjects, and the results of the perceptual imagery evaluation are shown in Figure 5.

As can be seen in Figure 5, the perceptual imagery scores of the pattern geometries of the 10 optimized lacquerware samples were 3.72 (traditional), 3.51 (stately), 4.05 (trendy), and 4.12 (chic), respectively. The optimized lacquerware pattern geometries give the viewer a sensory impression that tends to be trendy and chic.

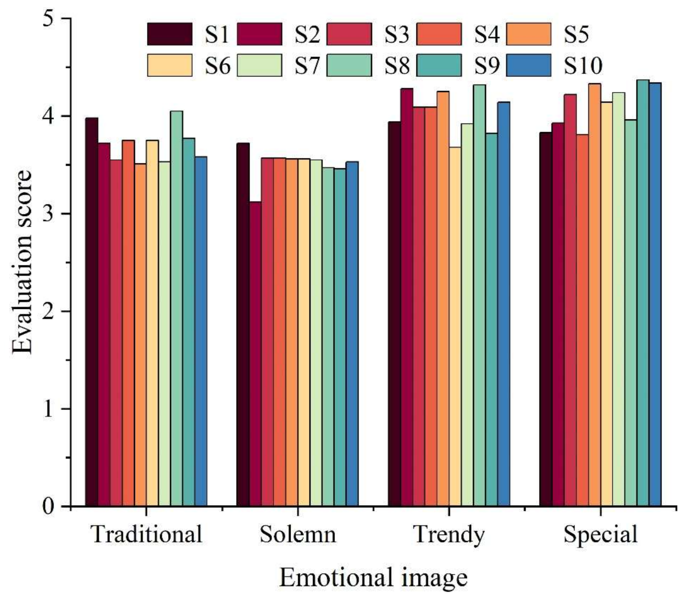

Figure 5: Emotional image evaluation results

V. Conclusion

The optimization method of lacquerware pattern geometry based on image recognition technology proposed in this study has achieved remarkable results. In pattern detection, the improved Canny algorithm combined with the HOG+SVM recognition model achieves high-precision pattern recognition, with a check accuracy rate of 94.44% and a recall rate of 96.02%, which proves the superiority of the method in the automatic recognition task of lacquerware patterns. In the pattern classification task, compared with the traditional networks such as VGG16 and ResNet50, the model in this paper improves 9.17% in accuracy and reaches the best performance of 94.73%. The lacquerware patterns optimized by the BP-GA algorithm show significant improvement in the evaluation of perceptual imagery, with the score of “trendy” perceptual imagery increasing from 3.67 to 4.05, and the score of “chic” from 3.90 to 4.12, which indicates that the optimized patterns are more in line with the modern aesthetic needs. The study provides effective technical solutions and theoretical support for the digital protection, intelligent design and innovative development of traditional lacquer art.

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