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Symbolic Re-creation and Brand Value Analysis of Mural Art in Brand Design Based on Graphic Recognition Algorithm

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Abstract As an important carrier of human cultural heritage, mural art contains rich visual symbols and national cultural connotations, which provides artistic reference for modern brand design. This paper takes mural art as the research object, and selects SIFT, a local feature description operator with good uniqueness of invariance, as the extraction algorithm of mural art features. The SC-SIFT descriptor is proposed by adding global features representing the shape space in the SIFT descriptor to enrich the acquisition information of feature description. After completing the optimization of the SIFT descriptor algorithm, the feature point pairs of the digital images of mural art are extracted using the SIFT algorithm, and the mural art feature extraction model based on SC-SIFT is constructed. On the basis of the acquired fresco feature data, the feature extraction as well as the analysis method of fresco art style is discussed. At the same time, combined with the characteristics of fresco art, the re-creation ideas and methods of fresco art symbols in contemporary brand design are elaborated. With the assistance of the SC-SIFT-based mural art feature extraction model and the re-creation thinking, the products designed by Brand K with mural art elements obtain a high average score of 7.36 in the cultural context dimension. This shows that the feature extraction model and re-creation method proposed in this paper can actively promote the re-creation and application of fresco art elements in brand design.

Index Terms mural art, SC-SIFT descriptor, graphic identity, brand design

I. Introduction

Mural painting is an ancient and unique art form that shows the viewer aspects of culture, history, and society by painting motifs and images on walls [1], [2]. These works of art are notable for their fine detail, vibrant colors, and rich social meanings [3]. As a unique and remarkable art form, they not only demonstrate culture and history through a diversity of expressions, but also convey far-reaching and lasting values [4]-[6]. From the point of view of artistic expression, frescoes have become the artistic enjoyment that the viewer's mind aspires to with its diversity, three-dimensionality and strong sense of space [7], [8]. And from the viewpoint of historical value, frescoes as witnesses and guardians carry the memory and pursuit of human social civilization [9], [10]. Therefore, frescoes are of great significance in promoting people's understanding of history, art appreciation and aesthetic education [11].

In modern brand design, by incorporating the art of frescoes is not only a design innovation, but also opens up a new path for the integration of traditional art and modern art [12], [13]. What is more valuable is that the application of mural art plays an important role in enhancing the value of the brand. Through the use of mural art elements, the brand design can incorporate the charm of traditional culture, enhance the market competitiveness of the product and the cultural connotation, and at the same time, promote the inheritance and innovation of traditional culture [14]-[17]. Therefore, in brand design, we should make full use of traditional art forms such as frescoes, combine traditional culture with modern design organically, and present consumers with more exquisite, recognizable and rich-connotation design works [18]-[20].

This paper firstly explains the basic interpretation of shape space representation and the extraction process of feature points by SIFT algorithm, and combines the two to construct SC-SIFT descriptor. Then, based on the fresco art feature data, it discusses the extraction of style features of fresco art elements and the analysis method. Subsequently, on the basis of fresco art elements and styles, combined with re-creation expression, the re-creation thinking of fresco elements is discussed. Finally, a similar algorithm comparison experiment and a feature extraction effect experiment are designed to evaluate the performance of the proposed model. The feasibility of the proposed model and method in design application is analyzed in the form of surveying audience groups and general consumers' satisfaction with fresco art products.

II. SC-SIFT based feature extraction model for mural art

II. A. SC-SIFT descriptor

The extended SIFT descriptor SC-SIFT proposed in this paper consists of two parts: a SIFT description vector that expresses the local features and a shape space that represents the global structural relationships of the feature points. It can be written in the form of Equation (1).

$$V_d = \begin{bmatrix} V_g \\ V_l \end{bmatrix} \tag{1}$$

V_g is a 60-dimensional global feature vector, and Eq. V_l is a 128-dimensional SIFT descriptor.

When feature point detection is performed, the method used is the same as SIFT feature detection, which also performs extreme point detection from Gaussian scale space and then eliminates unstable extreme points. Only the description of the feature points is different, SIFT descriptor pulls the previous way to establish: first determine the primary and secondary directions of the feature points, then rotate the surrounding neighborhood window to the primary direction, then establish the gradient histogram, and take the value of each gradient as a descriptor value.

II. A. 1) Description of the shape space

Inspired by the feature descriptors of shape space (which performs shape matching and object recognition), this paper proposes a very similar description of shape feature space.

Shape can be regarded as a collection of a series of feature points, and the shape of an object often consists of its edge points and corner points. Gaussian difference map can represent the shape of an object very well, and this paper is based on Gaussian difference map for shape characterization, without using other edge and corner detection operators, and without seeking the principal curvature of each point. The description of establishing shape features is performed in the following steps.

Take the absolute value of each point of the Gaussian difference map $D(x,y)$ where the feature points are located to get the Gaussian difference absolute map $absD(x,y)$, i.e., equation (2):

$$absD(x,y) = |D(x,y)| \tag{2}$$

For the detected feature point $A(x_0,y_0)$, the graph $absD$ is divided into 60 column blocks in polar coordinate space with A as the pole. The polar coordinate space is divided into 5 × 12 blocks by first delineating 5 columned surfaces centered on the coordinates of the pole, and then dividing each columned surface into smaller blocks with a circumferential angle of 30 degrees. Let d be the diagonal length of figure $absD$, then the diameter of each columned surface is in order of equation (3):

$$\frac{d}{16},\frac{d}{8},\frac{d}{4},\frac{d}{2},d \tag{3}$$

Assuming that the principal direction of the feature point $A(x_0,y_0)$ is θ, for each point $B(x,y)$ on the Gaussian difference absolute map, compute the block of columns in which it lies as in Eqs. (4)-(5):

$$\alpha = \left\lfloor \frac{6}{\pi}\left(\arctan\left(\frac{y-y_0}{x-x_0}\right)-\theta\right)\right\rfloor \tag{4}$$

$$\gamma = \max\left(1,\left\lfloor \log_2\left(\frac{2\|A-B\|}{d}\right)+1\right\rfloor\right) \tag{5}$$

(α,γ) is the index number of the column face block where the feature point is located, $0 \le \alpha \le 11, 1 \le \gamma \le 5$.

For each point B in Figure $absD$, given a weight, the closer to the feature point, the greater the weight and the greater the value of the contribution to the column in which it is located. The further away from the feature point, the smaller the weight and the smaller the contribution. The same as SIFT to establish the description of the neighborhood of the feature points when the weights are calculated, in this paper, the weights assigned to each point (x,y) also use the Gaussian window function as in equation (6):

$$w(x,y)=\frac{1}{2\pi\sigma^2}e^{-((x-x_0)^2+(y-y_0)^2)/(2\sigma^2)} \tag{6}$$

Thus for each point B, the corresponding column block (α,γ) is voted, i.e., the grayscale value of the point is multiplied by the corresponding weights accrued to that column block. To reduce the edge point effect, points on the boundary of a column surface are voted to the two column surfaces in the neighborhood to which they belong. Finally the histogram is then unitized.

The shape feature space of feature point A is the 5×12 muster histogram created according to the above steps.

II. A. 2) Analysis of SC-SIFT

In this paper, we propose the extended SIFT descriptor SC-SIFT, a linear combination of shape space vectors and SIFT descriptor vectors, combining the features of both descriptors.

The shape space has in-spin invariance and incomplete scale invariance. In fact, the shape space description of a feature point is computed by first rotating the entire Gaussian difference absolute map around the pole to the principal direction of the feature point. The realization does not require a rotation, but only the subtraction of a rotation angle. Thus the shape space descriptor is rotationally invariant.

The division of the polar column plane allows the shape space to adapt to certain scale variations, but the polar coordinate space divides the column plane according to the diagonal size of the image, unlike SIFT, which divides the column plane according to the scale factor of the feature points, and thus has only relative invariance in the scale transformation.

Therefore, SC-SIFT has rotational invariance and relative scale invariance. In mural object recognition, the images to be recognized are from compressed maps of high-precision murals, which do not vary much in scale, so the incomplete scale invariance of SC-SIFT does not affect the feature matching rate.

II. A. 3) SIFT algorithm feature point extraction

SIFT is an affective feature description algorithm based on scale space invariance, which has the advantages of rotation and scale invariance as well as robustness. Before matching and reconstructing the digital image, the algorithm is used to extract the feature points in the digital image, which improves the efficiency and accuracy of the subsequent feature matching and image reconstruction, and reduces the computational complexity of the algorithm. It is mainly divided into the following steps:

(1) Construct image pyramid. In order to extract the features of the digital image more comprehensively, the image sequence at different scales is obtained by performing multi-scale feature transformation on the denoised digital image. Denote the scale space of the denoised digital image by $Z(x_i,y_i,\zeta_o)$. Denote the original digital image by $O(x_i,y_i)$, and its convolution operation with the 2D Gaussian function $H(x_i,y_i,\zeta_o)$ with gradual change of scales results in Eqs. (7)-(8):

$$H(x_i,y_i,\zeta_o)=\frac{\hat{G}(a,b)}{2\pi\zeta_o^{2^{o+i/d}}}\exp\left(-\frac{(x-x_i)^2+(y-y_i)^2}{2\zeta_o^2}\right) \tag{7}$$

$$Z(x_i,y_i,\zeta_o)=H(x_i,y_i,\zeta_o)*O(x_i,y_i) \tag{8}$$

where ζ_o denotes the Gaussian scale function, o,t denote the number of groups of Gaussian pyramids and the number of layers in each group, respectively, and $o\in[0,1,\cdots,O-1],t\in[0,1,\cdots,d+2]$. "*" denotes the convolution operation.

Continuous downsampling is applied to the digital image of the penultimate layer of the i th group of the pyramid to obtain the digital image of the first layer of the $i+1$ th group of the pyramid. The number of layers of the pyramid is determined based on the size of the original digital image and the highest layer of the digital image, and the constructed image pyramid P is shown in Eqs. (9)-(10):

$$P=\log_2\{\min(Q,M)\}-l \tag{9}$$

$$l\in[0,Z(x_i,y_i,\zeta_o)\log_2\{\min(Q,M)\}] \tag{10}$$

where Q,M denotes the size of the original digital image. l denotes the logarithmic value of the size of the top digital image.

(2) Feature point detection. Since the Gaussian Laplacian function is more stable than the properties of gradient and angle of the digital image, and the Gaussian Laplacian function is similar to the Gaussian difference function after the normalization of the scale, the Gaussian difference digital images at different scales (DOG) are formed

into a Gaussian digital image difference pyramid P for detecting its extreme values. The local extreme points of the digital image are obtained by comparing each pixel on each layer of the image from the 2nd to the penultimate layer in the DOG space with the neighboring 26 pixel sizes.

(3) Feature point localization. The above feature point detection can only obtain a set of discrete feature points, while in the real space, the location of the feature points needs to be determined by the implementation of the interpolation fitting operation. Therefore, the scale function of DOG is subjected to the subterm element interpolation operation, which results in the Taylor expansion of the DOG function as in Eq. (11):

$$F(X)=F(X_0)+\frac{\partial F^T}{\partial X}X+\frac{X^T}{2}\frac{\partial^2 F}{\partial X^2}X, \tag{11}$$

where X denotes the position vector of the extreme point and X_0 denotes the initial position vector of the extreme point. Set $F(X)=0$ to obtain the offset vector of the extreme point as in equation (12):

$$\bar{X}=-\frac{\partial^2 F^{-1}(X)}{\partial X^2}\frac{\partial F(X)}{\partial X} \tag{12}$$

The offset vector $F(\bar{X})$ of the extreme points of the DOG function is obtained by calculation, and if $F(\bar{X})$ is smaller than a set threshold, it is eliminated.

For the problem that the extreme points of DOG operator at the edges of digital images are very unstable, a kind of principal curvature threshold is set for the extreme points on the edges, so that the obtained values are maintained within the threshold range, and they are eliminated if they exceed the threshold.

(4) Feature point direction matching. After obtaining the feature point position information, in order to ensure the stability of the feature point in the process of rotation, it is necessary to analyze the direction orientation of the feature point. The gradient distribution value calculation is implemented on the digital image, and the gradient modulus value $q(x_i,y_i)$ and the direction $v(x_i,y_i)$ of the feature point at (x_i,y_i) are shown in equations (13)-(14):

$$q(x_i,y_i)=\sqrt{(Z(x_i+1,y_i)-Z(x_i-1,y_i))^2+(Z(x_i,y_i+1)-Z(x_i,y_i-1))^2} \tag{13}$$

$$\vartheta(x_i,y_i)=\tan^{-1}\frac{Z(x_i,y_i+1)-Z(x_i,y_i-1)}{Z(x_i+1,y_i)-Z(x_i-1,y_i)} \tag{14}$$

According to a certain order, the circular neighborhood of a given radius is divided into 36 sub-directions on average, and each sub-direction contains information about the gradient values within 10°, and the group with the largest cumulative gradient value is obtained by using a statistical method, and the main direction of the feature point is determined by the parabolic interpolation algorithm.

(5) Feature descriptor determination. The radius of the feature points in the neighborhood region is divided into 4×4 sub-areas, and the cumulative gradient values are calculated in each sub-area to obtain a 128-dimensional vector, which is used as the feature descriptor J for the feature point pairs. It is normalized so as to obtain the final digital image feature point pair J_q as in equation (15):

$$J_q=\frac{j_q q(x_i,y_i)}{\vartheta(x_i,y_i)\sqrt{\sum_{m=1}^{128} j_m^2}}, q=1,2,\cdots,128 \tag{15}$$

II. B.Feature Extraction and Analysis of Artistic Styles

(1) Angle between segments

To find the angle between two strokes, you need to fit them, the methods are endpoint line fitting, endpoint line translation fitting, least squares fitting, etc.. At first, we have to do a straight line fit to the two strokes that are close to each other, and then find their slopes after fitting them. The method used in this paper is the least squares method.

The steps of the method used here are firstly to fit the points $(x_i,y_i)(i=1,2,3...n)$, make a fit $y=b+ax$, and find a, b such that equation (16):

$$J(b,a)=\sum_{i=1}^{n}[y_i-(b+ax_i)]^2 \tag{16}$$

From equation (16) there are equations (17)-(18):

$$\frac{\partial J}{\partial b}=\sum_{i=1}^{n}2[y_i-(b+ax_i)]=0 \tag{17}$$

$$\frac{\partial J}{\partial a}=\sum_{i=1}^{n}2[y_i-(b+ax_i)](-ax_i)=0 \tag{18}$$

(19)-(20) from Eqs. (17)-(18):

$$nd+a\sum_{i=1}^{n}x_i=\sum_{i=1}^{n}y_i \tag{19}$$

$$b\sum_{i=1}^{n}x_i+a\sum_{i=1}^{n}x_i^2=\sum_{i=1}^{n}x_iy_i \tag{20}$$

Calculating a and b, $y=b+ax$ is the fitted line. After fitting the strokes, the formula is obtained, which is used to find the angle of entropy, and the value obtained is the angle of entropy to be obtained.

(2) Slope and curvature

Slope K indicates the general direction of the author's strokes. The method of its calculation is the relative power-off position of the two strokes. Any stroke is formed with initial and end points. By connecting the initial and end points, the corresponding slope value can be obtained by calculating the value. Connecting the initial and end points, a straight line is obtained, and the general direction of the author's stroke is obtained by calculating the slope of that straight line. Setting the initial and end points $(x_a, y_a),(x_b, y_b)$, the formula for calculating the slope is equation (21):

$$k=\frac{y_b-y_a}{x_b-x_b}\ \&\ c=\frac{|p_bp_{b+1}|+...+|p_{c-1}p_c|}{|p_bp_c|} \tag{21}$$

where $|p_ip_j|$ is the similarity distance between the point p_i and the point p_j.

(3) Perturbation degree

The relative perturbation degree of the strokes is a manifestation of the characteristics of the starting and finishing strokes, which is an element that reflects the style of the artist. The perturbation degree is defined as the area of the skeleton circumference and is calculated as in equation (22):

$$f_{\mathrm{var}}=\sum_{i=0}^{n}\frac{|Ax_i+By_i+C|}{\sqrt{A^2+B^2}} \tag{22}$$

where $A=y_{ie}-y_{ib}, B=x_{ib}-x_{ie}, C=x_{ib}y_{ie}-x_{ie}y_{ib}$.

(4) Geometric feature extraction

1) Area S and perimeter L

The size of a shape is commonly expressed in terms of perimeter, area. These two values are for binary images, i.e., $f(i,j)=1$ if a pixel is part of an object. For all non-object pixels or background pixels, $f(i,j)=0$. The area and perimeter of any module are obtained by computing the area and perimeter of the module, and these two values are compared as a way to get the properties characterized by the module.

Roughly speaking, the area S species the same number. The L of a module is the sum of the lengths of the individual points. A perimeter L is any point, and all the boundaries are calculated starting from this pixel point until the end point. The sum of all the pixel points experienced is the required perimeter. The area S of each object within the image is the number of all pixels in the region $f(i,j)=1$.

2) Circularity, endocircle radius and shape complexity

All shapes that are circular can be represented by the circularity R_0. It is found using equation (23):

$$R_0=4\pi S/L^2 \tag{23}$$

where s and L are the area and perimeter of the figure, respectively, and the range of R_0 is expressed as $0\le R_0\le 1$, and a large R_0 indicates that it is circle-like. Select Triangle, Circle, Square and set a value: 1, 0.79 and 0.60.

The radius r of the internal tangent circle is as in equation (24):

$$r = 2S / L \tag{24}$$

The complexity is replaced by the exponent e, calculated as in equation (25):

$$e = L^2 / S \tag{25}$$

The size of e represents the circumference of a circle, and as it gets larger, it means that the longer the shape is, the more complex the shape is, and if it gets smaller, it is the opposite of the above. By calculating the above mentioned to three typical shapes, the values obtained are: circle e = 12.6. Square e = 16.0. Triangle e = 20.8.

III. Re-creative thinking of mural elements

Visual expression is "re-creation of expression", especially in traditional Chinese graphic design. It originates from tradition and cannot be separated from the specific cultural background. It provides a specific space for the creation of meaning of visual symbol expression and design, and changes and develops with the development of the times. Modern graphic design takes the development of national traditional culture as a foothold, based on the reality of the cultural context, diversification, personalization and development into harmony, transforming the dormant tradition into a new impetus for innovation and development, and expanding and extending the modern space.

In addition to drawing on traditional Chinese cultural resources for themes and expressions, the works of contemporary designers are also clearly influenced by the digital technologies of the information age. New media and new technologies have given the fusion of the two a more realistic cultural context. "Art, as a mode of production, has the greatest intersection and adhesion with other modes in today's social operating system." The same is true for visual communication design, which is currently not the only way of existence, but rather a synthesized hybrid product. It seeks resources in different ways, including the fruits of high technology, but also includes the transformation and utilization of excellent traditional cultural heritage, and even the integration of "ideas" and traditional resources to create and innovate forms of visual expression, all of which are newly developed modern design drawing on traditional cultural resources.

In the midst of major social changes, traditional Chinese visual symbols and pattern elements were proposed and applied to a social behavior, namely graphic design, which is closely related to society. The change and progress of design concepts and design visual language implies the inheritance and elimination of tradition. The expansion and re-expansion of traditional cultural resources is a process of taking and removing things, and the works have a contemporary flavor. Combining new forms with traditional symbols, combining tradition with modernity, makes them collide with more brilliant artistic fire. For example, the image of the nine-colored deer commonly seen in murals signifies beauty and wisdom in traditional Chinese culture. Applying the nine-colored deer element in visual communication design, attention should be paid to re-create the antlers, neck, eyes, hair and other details of the nine-colored deer. For example, Dunhuang cultural and creative series of tea cups cup wall used nine-colored deer elements, its color is more consistent with the original Dunhuang paintings, mainly white, and colorful light strokes outlined. And in the character shape, long limbs, neck straight, set the beauty of the slender and the beauty of strength in one, a blend of the West and the aesthetic characteristics of the Central Plains.

IV. Test and application of feature extraction model for mural art

This chapter starts from two perspectives: the performance of the model and the application performance, and examines the performance of the model in the form of comparison of similar algorithms and evaluation of the effect of feature extraction, and evaluates the application value of the model in the form of investigation of the brand audience groups and general consumers' satisfaction with the products of the mural art elements.

IV. A. Performance test of the model

IV. A. 1) Comparative experiments and analysis of similar algorithms

Nine feature extraction like algorithms are selected:(X1)YOLOv5s-seg, (X2)YOLOv5m-seg, (X3)YOLOv5l-seg, (X4)YOLOv5s-seg+EIoU-Foacl, (X5)YOLOvSs-seg+DIoU-NMS, (X6)YOLOv5s-seg+ DIoU+BOTNet, (X7) YOLOvSs-seg+EIoU+BOTNet, (X8) YOLOvSs-seg+-Focal-EIoU+B, and (X9) OTNet, unfolding the comparison of the operational performance metrics with (X10) this paper's model is shown in Table 1.

The size of the model is related to the stability and running speed of the model operation. Observing Table 1, the mAP value of the mural art feature extraction model based on SIFT algorithm proposed in this paper is the highest, which is 0.913, and the size is moderate, which is 7.2 M. It shows that the model in this paper can combine both the high-precision extraction of feature points and the stability of the model.The visual comparison of the mAP values and sizes of the 10 models is shown in Fig. 1.

Table 1: The mAP, GFLOPs and model sizes of 10 models

Model	mAP@0.5	PARAMS(m)	GFLOPs
X1	0.887	7.5	25.8
X2	0.896	21.8	69.9
X3	0.908	88.4	146.5
X4	0.892	7.5	25.8
X5	0.623	7.5	25.8
X6	0.886	7.2	25.5
X7	0.895	7.2	25.5
X8	0.896	7.2	25.5
X9	0.901	7.2	25.5
X10	0.913	7.2	25.5

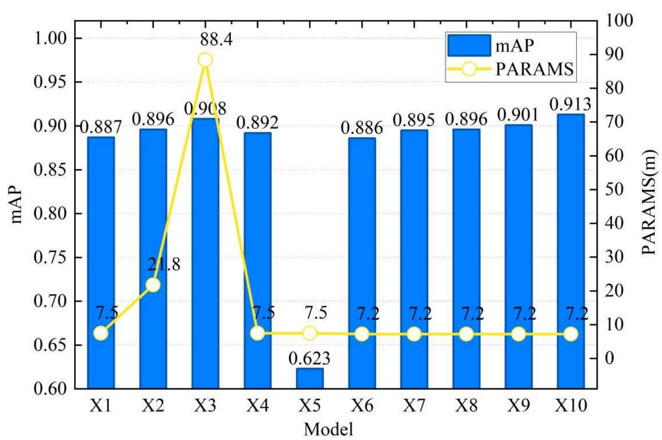

Figure 1: Comparison of mAP values and model sizes of 10 models

IV. A. 2) Evaluation of the effectiveness of the model's feature extraction

The randomly sampled results of the feature extraction model of this paper on the feature recognition of 20 categories of different themes in the Dunhuang mural painting data set are plotted in Fig. 2. The sampled 20 categories are, in order: nine-colored deer, guardian dragon, blue bird, Baoxiang flower, lotus lotus, Lonicera, peony twining branches, pomegranate curling grass, double dragons spitting pearls, winged horse, auspicious clouds, waist drum, conch, algae well, phoenix bird, three rabbits with ears, eight leaves and nine Buddhas, Guanyin statue, multi-headed flame and Flying Sky.

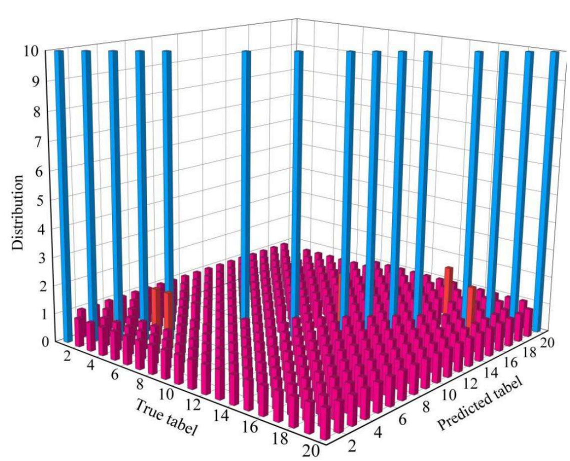

Figure 2: The similarity situations of 20 categories

Since the distribution of all categories is not completely plotted, the diagonal distribution presents a discontinuous shape, as some samples are incorrectly identified as non-sampled categories. From Fig. 2, it is easy to see that the majority of images from the 20 sampled categories are accurately recognized as the corresponding category, but a small number of bird samples belonging to category label 4 are outputted by the model with labels 5 and 6. In the Dunhuang mural painting dataset, the pattern with category label 4 is Baoxiang flower, and the pattern with category labels 5 and 6 is lotus flower and Lonicera flower, respectively, and these misclassified images have high similarity with each other. It can be seen that the SC-SIFT-based mural art feature extraction model designed in this paper has a high accuracy in the overall extraction of mural art symbol features, but it needs to be refined in the recognition and extraction of some more similar patterns.

IV. B. Practical application of the model

Mural art elements of product design is a quality of its cycle and optional generation, design program output arrives at the end of the test phase, after testing and feedback can once again be substituted into the process of repeating the service thinking, and constantly improve and refine the solution.

This paper takes a national brand K as an experimental object, and uses SC-SIFT-based mural art feature extraction model to obtain mural element feature data. Under the guidance of fresco element recreation thinking, the symbol design and recreation of fresco art elements of the brand are carried out. After the mural art element design scheme was formed, the brand audience including 89 loyal consumers and 9 brand management personnel were selected to conduct a satisfaction survey. An overview of the interviewees is shown in Table 2.

Table 2: Interviewee Profile

Occupational composition	Gender	Number of people
Design the management level	Woman	7
	Man	2
Company employee	Woman	28
	Man	9
Individual household	Woman	2
	Man	9
Teacher	Woman	15
	Man	3
Freelance work	Woman	7
	Man	2
Student	Woman	5
	Man	0

IV. B. 1) Survey of Consumer Preferences

Figure 3 shows the results of the survey on the consumption preference of 89 brand audiences based on the recreation of mural art elements, and the consumption preferences are divided into four ranges: 0-500 yuan, 501-1000 yuan, 1001-2000 yuan and more than 2000 yuan according to the product pricing range of the brand. Among the 89 audiences, 26 people preferred 0-500 yuan, 39 people preferred 501-1000 yuan, 15 people preferred 1001-2000 yuan, and 9 people preferred more than 2000 yuan.

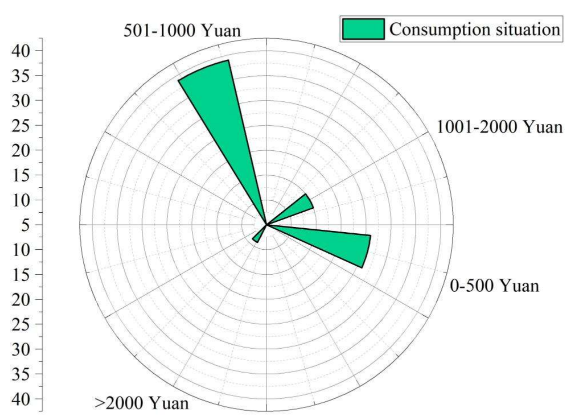

Figure 3: The consumption preferences of the brand's audience

IV. B. 2) Satisfaction surveys

Combined with Richter's five-point scale, satisfaction was categorized into five grades: satisfied (5 points), more satisfied (4 points), average (3 points), less satisfied (2 points), and more dissatisfied (1 point). Through open meetings and online exhibitions, the design proposal and finished product of this mural art element were presented to 89 audiences. A satisfaction questionnaire for this mural art symbol design program was issued to 89 audiences around 10 indicators: (D1) artistry, (D2) innovativeness, (D3) mural symbols, (D4) practicality, (D5) aesthetics, (D6) cultural connotations, (D7) acceptance, (D8) design styles, (D9) consumption desire, and (D10) overall satisfaction. A total of 89 questionnaires were distributed, 89 valid questionnaires were recovered, and the validity rate of the questionnaires was 100%.

89 audiences in the 10 indicators on the distribution of the number of ratings are shown in Figure 4, based on Figure 4 calculated (D1)-(D10) the average score of the ten indicators in turn: 4.31, 3.42, 3.06, 3.27, 3.75, 3.49, 3.69, 3.74, 3.80, 3.78. 89 audiences in the 10 indicators on the average average average of 3.00 and above, of which (D1)-(D10) the average of 3.00 and above, of which (D1) the average of the 10 indicators on the average of 3.00 and above, of which (D1) the average of the 10 indicators on the average average of 3.00 and above, of which (D1) the average of the 10 indicators of 3.00 and above. The average value of 89 audiences on 10 indicators is above 3.00, and the average value of (D1) artistry is as high as 4.31, which indicates that consumers agree with the artistry and design form of the mural symbols produced by the feature extraction model of this paper and the re-creative thinking, and the overall satisfaction is not low. This indicates that the model and the re-creation method designed in this paper can assist the re-creation application of fresco art elements in brand design.

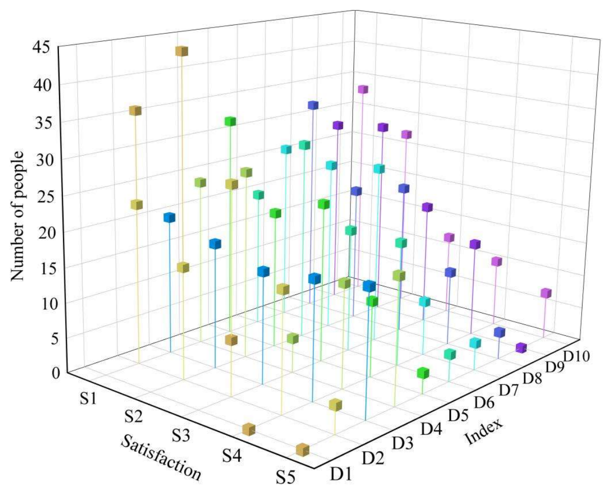

Figure 4: Satisfaction Survey on Mural Symbol Design

IV. B. 3) Assessment of design effectiveness

In order to further verify whether the design of the mural art elements of Brand K meets the different dimensions of consumers' embodied needs, 150 ordinary consumers were selected as experimental subjects. The questionnaires were distributed through an online platform, and the questionnaires consisted of three embodiment dimensions, namely, (E) perceived contact, (F) usage experience, and (G) cultural context, where the (E) perceived contact dimension mainly assessed the styling and coloring of the finished product as well as the material mechanism, the (F) cultural context mainly assessed the consumers' cultural identity and psychological resonance of the design, and the (G) usage experience mainly assessed the consumers' experience of using the product and their overall satisfaction with it. The questionnaire contains 30 questions to assess the consumers' cultural identity and psychological resonance towards the design. The questionnaire contains a total of 30 assessment questions, with 1~10 points to express the degree of satisfaction with the mural art elements of a measurement item, including very dissatisfied: 0-2 points, dissatisfied: 3-4 points, general: 5-6 points, satisfied: 7-8 points, very satisfied: 9-10 points. A total of 150 questionnaires were distributed, 143 valid questionnaires were returned, with a validity rate of 95.33%. 143 general consumers' satisfaction with the artistic elements of K brand murals is shown in Figure 5. Based on Figure 5, it can be calculated that the 143 average consumers have a mean score of 6.49 on dimension (E) Perceived Exposure, 5.12 on (F) Usage Experience, and 7.36 on (G) Cultural Context.

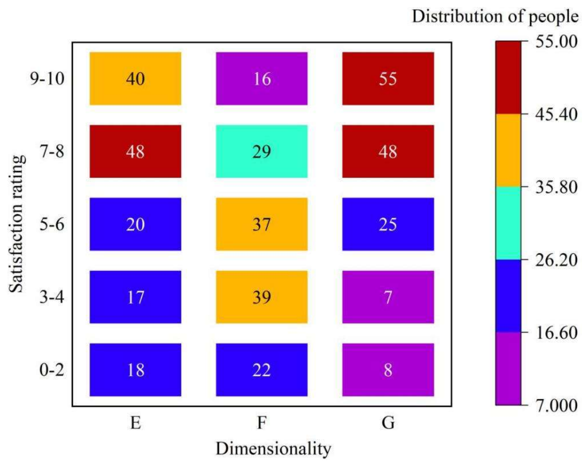

Figure 5: Satisfaction survey of ordinary consumers

According to the scoring, the surveyed consumers can be divided into three categories: 0~4 as critics, who are dissatisfied with the design of the mural art elements; 5~6 as neutrals, who maintain a neutral attitude towards the design of the mural art elements; and 7~10 as recommending supporters, a group of adolescents who are highly satisfied with the design of the mural art elements and are happy to recommend it to people around them. Further, the NPS score can be found, that is, the proportion of supporters minus the proportion of critics, which results in an NPS score of 37.06% for Dimension (E) Perceived Exposure, an NPS score of -11.19% for Dimension (F) Cultural Context, and an NPS score of 61.53% for Dimension (F) Cultural Context.

Comprehensive analysis of the above can be found that both brand audiences and ordinary consumers show high satisfaction with the image and cultural content design of the mural art elements, reflecting the feasibility of the feature extraction model and re-creation thinking method designed in this paper in practical application. At the same time, however, the products of the designed mural art elements are generally evaluated in practical use, which requires the brand to pay attention to the quality control of the products in the production.

V. Conclusion

In this paper, the SC-SIFT descriptor is designed to realize the global extraction of the content of the elements of the fresco art by adding the representation of shape space to the SIFT descriptor. Based on the extracted fresco art feature data, the art style features are extracted and analyzed to provide reference elements for the recreation of this fresco art. This completes the construction of the mural art feature extraction model based on SC-SIFT.

The mAP value of the mural art feature extraction model based on the SIFT algorithm is 0.913, the size of the model is only 7.2M, and the extracted mural art elements have a high degree of similarity with their original paintings. The products with fresco art elements get the highest average score of 4.31 for the artistry index of the brand audience group, and the highest average score of 7.36 for the cultural context dimension of the general consumer group. The model is not only superior to similar algorithms in operation, but also capable of extracting and designing the characteristic elements of mural art with high precision, which assists in the re-creation and value embodiment of mural art elements in brand design.

References

[1] Lian, J., Zhang, J., Du, S., Liu, Q., & Liu, J. (2025). Adversarial Diffusion Network for Dunhuang Mural Inpainting. IEEE Transactions on Circuits and Systems for Video Technology.

[2] Susanto, D., Widyarko, W., & Ilmiani, A. N. (2017, December). Mural art as a media on making urban kampung's public space. In IOP Conference Series: Earth and Environmental Science (Vol. 99, No. 1, p. 012019). IOP Publishing.

[3] Prasiasa, D. P. O. (2022). Mural art as a media for social criticism: perspective structuralist-constructivism. Mudra Jurnal Seni Budaya, 37(2), 203-211.

[4] Abd Rahman, N., Ismail, A. R., & Abdul Rahim, R. (2020). Revolutions of Mural Painting. International Journal of Academic Research in Business and Social Sciences, 10(10), 1195-1200.

[5] Alikhanzadeh, M. (2020). The role of mural art in the development of cultural tourism. Journal of Urban Studies on Space and Place, 1399(16).

[6] Aryanti, S. Z., Nasucha, Y., & Al-Ma'Ruf, A. I. (2020). Mural Art Media F0R Millennials Character Education. JMM (Jurnal Masyarakat Mandiri), 4(3), 475-482.

[7] Liu, X., Wang, Y., Zhang, J., Pan, D., & Chang, Y. (2024). National culture symbols in murals of China: Chinese public art as a synthesis of aesthetics and politics of China/Símbolos de la cultura nacional en los murales de China: el arte público chino como síntesis de la estética y la política de China. Culture and Education, 36(2), 346-369.

[8] Jingfeng, Q. I. (2014). The Functions of Modern Mural Art. Cross-Cultural Communication, 10(2), 25.
[9] Liu, C., Bakar, S. A. S. A., & Ismail, I. (2024). Application Study of Chinese Traditional Mural Materials in Comprehensive Material Painting. International Journal of Creative Future and Heritage (TENIAT), 12(2), 1-16.
[10] Wang, Y., & Wu, X. (2023). Current progress on murals: distribution, conservation and utilization. Heritage Science, 11(1), 61.
[11] Okafor, K. A. (2024). MURAL ARTS IN ANAMBRA STATE-NIGERIA. ESTAGA: JOURNAL OF INTERDISCIPLINARY PERSPECTIVES, 1(2).
[12] MOHAMED ALI SHAHIN, A. S. M. A. A. (2021). The Mural Design Derived From Heritand its Impact on The Development of Community Culture. International Journal of Multidisciplinary Studies in Heritage Research, 4(1), 69-103.
[13] Yarc, M. (2019). Mural Mural on the Wall: Revisiting Fair Use of Street Art. UIC Rev. Intell. Prop. L., 19, 267.
[14] Biciuşcă, E. R. (2024). Monumental Mural Art And Ceramics Today. Anastasis: Research in Medieval Culture & Art, 11(1).
[15] Zhang, J. (2021). Exploring the application of traditional elements in cultural and creative product design. Art and Design Review, 9(4), 332-340.
[16] Zhang, Y. (2022, February). The Application and Practice of Traditional Cultural Symbols in the Brand Design of "Nation Tide". In 2021 conference on art and design: Inheritance and innovation (ADII 2021) (pp. 266-270). Atlantis Press.
[17] Liu, J., Krotova, T. F., Yezhova, O., & Pashkevich, K. (2018). Traditional elements of Chinese culture in logo design. International Circular of Graphic Education and Research.
[18] Zhang, M., & Wang, Z. (2024). Running Head: The Fusion Of Chinese Traditional Culture And Modern Design The Fusion of Chinese Traditional Culture and Modern Design: Exploring Balance and Conflict Resolution in a Globalized Context. Library of Progress-Library Science, Information Technology & Computer, 44(3).
[19] Huang, Z., & Jung, E. (2024). Analyzing the Application of Traditional Chinese Cultural Elements in Brand Packaging Design With Design Semiotics: A Case Study of Modern China Tea Shop. Psychology, 14(7), 215-222.
[20] Fan, H. (2023). The heritage and promotion of traditional tea culture by brand design in the context of national trend. Journal of Sociology and Ethnology, 5(7), 130-138.