International Journal for Housing Science and Its Applications
Publish August 4, 2025. Volume 46, Issue 3 Pages 1822-1834

https://doi.org/10.70517/ijhsa463144

Random Forest Algorithm-Based Mural Image Style Migration and Cultural and Creative Product Design in the Context of Cultural and Tourism Integration

Yun Qiu[1,*], Nan Shi[2,3] and Mastura Haji Mohd Jarit[4]
[1] Chodang University, 380 Muan-myeon, Muan-eup, Muan-gun, Jeollanam-do, 58530, Republic of Korea
[2] College of Creative Art, Changji College, Changji, Xinjiang, 831100, China
[3] College of Creative Art, Universiti Teknologi MARA, Shah Alam, Selangor, 40450, Malaysia
[4] Universiti Teknologi MARA, Creative Art, Shah Alam, Selangor, 40450, Malaysia
Corresponding authors: (e-mail: yunqiu180@gmail.com).

Abstract Aiming at the difficult problem of color distortion and style adaptation of mural images in the context of cultural and tourism integration, this study proposes a mural style migration model based on the fictionalizable Random Forest algorithm, which is combined with the CycleGAN framework to design a multi-component loss function to achieve a balance between content fidelity and artistic style. The random forest algorithm is improved by joint optimization of probabilistic decision nodes and leaf nodes, path length regularization (PPL) is introduced to control the model complexity, and traceable color profiles are constructed to support mural protection and cultural and creative design. The experimental results show that the proposed model RF-CycleGAN significantly outperforms the comparison algorithm in terms of FID of 175.891 and KID of 0.0233, and the user score reaches 4.08 (out of 5), and the "image appearance" and "style simulation" dimensions in the expert evaluation are 4.08 (out of 5) respectively. The dimensions of "image appearance" and "style simulation" in the expert evaluation score 4.20 and 4.10 respectively. Based on the migrated mural images, we further propose the cultural and creative product design strategy driven by cultural symbols, visual styling and color system, and verify the application value of the model in the living communication of cultural heritage.

Index Terms random forest, CycleGAN, mural images, style migration, cultural and creative products

I. Introduction

With the continuous development of tourism, the integration of culture and tourism has gradually become a trend [1], [2]. The integration of culture and tourism refers to the phenomenon and process of interpenetration, cross-confluence and reorganization between culture, tourism industry and related elements, gradually breaking through the original industrial boundaries or elemental fields, and intermingling with each other to form a new symbiosis [3]-[5]. In the integration of culture and tourism, tourism is no longer just simple sightseeing and excursion, but pays more attention to cultural experience and creative innovation [6]-[8]. At the same time, the cultural industry is no longer a single artistic creation, but covers a variety of links such as design, production and marketing [9], [10]. As an important part of culture, mural painting is an important form of promoting the development of cultural tourism integration through the integration of image style migration and cultural and creative product design in the context of cultural tourism integration [11]-[13].

As an important part of Chinese traditional culture, mural painting has extremely profound historical precipitation and cultural connotation [14], [15]. Mural image style migration is to synthesize a new image by combining the content of a mural image with the style of another image [16]. With the rise of cultural and creative industries, mural elements have become the favorite creative inspiration for designers [17], [18]. Its rich patterns, unique colors and cultural connotations provide rich resources for cultural and creative product design [19]. Applying mural elements to cultural and creative product design can not only inherit and promote traditional culture, but also give historical emotions and cultural weight to the products, and enhance the added value and attractiveness of the products [20]-[22].

In this study, we propose a fresco style migration model based on fictional random forests, aiming to solve the problem of color distortion and promote the intelligence of cultural and creative product design. The difficulties and importance of accurate color correction of frescoes are explained, and the technical bottlenecks of color correction in fresco digitization are analyzed, emphasizing the fundamental role of color information for fresco conservation, restoration and subsequent research. Through the establishment of traceable color profiles, a quantitative basis for preventive conservation is provided. On this basis, an improved random forest algorithm is proposed to achieve end-to-end microscopicity of the model through the joint optimization of probabilistic decision nodes and leaf nodes. The gradient optimization strategy of decision tree parameters (e.g., routing function, loss function) is derived in detail to support back-propagation training. And we construct a random forest-based mural style migration model to control the model complexity by introducing path length regularization (PPL), and avoid overfitting by separating the update frequency of the main loss and the regularization term. Multi-component losses are designed in combination with CycleGAN framework, including adversarial loss and cyclic consistency loss, to ensure the balance between content fidelity and style adaptation in style migration.

II. Modeling of style migration driven by micro-random forests

II. A. Difficulties and importance of accurate color correction of wall paintings

In order to obtain high-definition and high-fidelity digital images of murals, it is necessary to perform image color correction, image deformation correction, image splicing and other operations on the basis of image acquisition. In this process, image color correction is one of the most difficult problems, mainly due to the intricacies of the factors that cause color changes in digital images. For example, the light source illuminates the surface of the mural, and the color information is finally obtained by the observer or the digital acquisition device, in this process, even if different observers see different color information, due to the unknown color rendering of the light source, the unknown color characteristics of the surface of the mural, the unknown color response of the acquisition device to the color, the color of the surface of the mural is to accurately determine the color information of the surface of the mural in such a complex relationship with a strong coupling In such a complex relationship with strong coupling, to accurately determine the color information of fresco surface is an extremely difficult problem.

At the same time, the color correction of mural images is an extremely important and meaningful problem. Firstly, the color information can directly reflect the relevant nature of the mural paintings; secondly, the color difference and change is also an important indicator in the conservation of mural paintings, from the beginning of the excavation of mural tombs, the intuitive change of the color of the surface of the mural paintings is well known, but how much the specific color change, the rate of color change and the distribution of the color is little known. The need to establish a unified benchmark, traceable color archives, which is also a key issue in the preventive research and protection of cultural relics color; third, the color correction of mural images is a key step in obtaining high-definition and high-fidelity digital images of murals, and it is the basis for the subsequent mural image deformation correction and accurate splicing.

II. B. Microscopic Random Forests

Despite the many challenges of mural color correction, its importance requires us to explore more efficient solutions. To this end, this section introduces the fiducializable random forest algorithm, which provides a new paradigm for modeling complex color mapping relationships through a probabilistic decision-making mechanism with end-to-end optimization.

Suppose a classification problem with input and output spaces X and Y, respectively, and denote by N the index of the internal nodes of the decision tree and by L the index of the leaf nodes. For each prediction node (i.e., leaf node) $\ell \in \mathrm{L}$ maintains a probability distribution π_ℓ on Y, and each decision node (i.e., internal node) $n \in \mathrm{N}$ has a decision function $d_n(\cdot;\theta): \mathrm{X} \to [0,1]$, with parameter θ, which serves to pass samples through the decision tree. When the sample $x \in \mathrm{X}$ reaches the decision node n, it will be passed to either the left or right subtree depending on the output of $d_n(x;\theta)$. The direction of passing in this is generated by a Bernoulli random variable with mean value $d_n(x;\theta)$. When the sample reaches the prediction node ℓ, the output of the associated decision tree is given by the distribution of class labels π_ℓ, and the final class prediction will be given by the average probability of reaching the class prediction node. Then for a tree T with decision node parameter θ, the final prediction for sample x is:

$$\mathrm{P}_T\left[y \mid x,\theta,\pi\right] = \sum_{\ell \in \mathrm{L}} \pi_{\ell_y} \mu_\ell\left(x \mid \theta\right) \tag{1}$$

where $\pi = (\pi_\ell)_{\ell \in \mathrm{L}}$, π_{ℓ_y} denotes the probability that the sample reaches the leaf node ℓ and is of class y, and $\mu_\ell(x \mid \theta)$ denotes the routing function of the sample x to the leaf node ℓ. Clearly for all $x \in \mathrm{X}$, clearly $\sum_\ell \mu_\ell(x \mid \theta) = 1$.

The routing function μ_ℓ is defined as follows:

$$\mu_\ell(x \mid \theta) = \prod_{n \in \mathrm{N}} d_n(x;\theta)^{1_{n\ell}} \left(1 - d_n(x;\theta)\right)^{1_{nr}} \tag{2}$$

where nl denotes true if the leaf node ℓ belongs to the left subtree of the decision node n and false otherwise, and nr denotes true if the leaf node ℓ belongs to the right subtree of the decision node n and false otherwise. 1_p denotes the indicator function conditional on P, i.e:

$$1_p = \begin{cases} 1 & p = True \\ 0 & p = False \end{cases} \tag{3}$$

The definition of the decision function $d_n(x;\theta)$ is given below:

$$d_n(x;\theta) = sigmoid\left(f_n(x;\theta)\right) \tag{4}$$

where $f_n(x;\theta)$ is a real-valued function that can be considered as a linear output unit of the deep network. It is converted into a probabilistic route by applying the $sigmoid$ function through d_n and mapped in the range of $[0,1]$. A single probabilistic decision tree is shown in Figure 1.

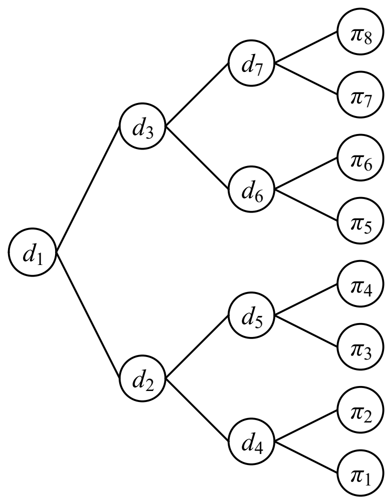

Figure 1: Single probabilistic decision tree

For a decision forest, which is a collection of decision trees, let the decision forest $\mathrm{F} = \{T_1, T_2, \ldots, T_k\}$, whose output for a sample x be the mean of the decision tree output:

$$\mathrm{P}_{\mathrm{F}}[y \mid x] = \frac{1}{k}\sum_{h=1}^{k} \mathrm{P}_{T_h}[y \mid x] \tag{5}$$

The following describes how to learn a tree by backpropagation. The parameters to be learned in a decision tree are the decision node parameter θ and the leaf node predicted value π. Learning of these two parameters follows the minimum empirical risk for a given dataset $\mathrm{T} \subset \mathrm{X} \times \mathrm{Y}$ under the log loss condition, with the empirical risk R defined as:

$$R(\theta,\pi;\mathrm{T}) = \frac{1}{|\mathrm{T}|}\sum_{(x,y)\in\mathrm{T}} L(\theta,\pi;x,y) \tag{6}$$

where $L(\theta,\pi;x,y)$ is the logarithmic loss of the training sample $(x,y)\in\mathrm{T}$ with the following formula:

$$L(\theta,\pi;x,y) = -\log\left(\mathrm{P}_T[y \mid x,\theta,\pi]\right) \tag{7}$$

The optimization process employs a two-step optimization strategy that alternately updates θ and π to minimize the empirical risk R.

For the parameter θ, all the decision functions $d_n(x;\theta)$ depend on this one common parameter, and also for each $f_n(x;\theta)$ in Eq. (4) is coupled through the parameter θ, and the optimization of the parameter θ is adopted by the gradient descent method (SGD).

$$\begin{aligned}\theta^{(t+1)} &= \theta^{(t)} - \eta \frac{\partial R}{\partial \theta}\left(\theta^{(t)}, \pi; \mathrm{B}\right) \\ &= \theta^{(t)} - \frac{\eta}{|\mathrm{B}|} \sum_{(x,y)\in \mathrm{B}} \frac{\partial L}{\partial \theta}\left(\theta^{(t)}, \pi; x, y\right)\end{aligned} \tag{8}$$

where $\eta > 0$ is the learning rate and $\mathrm{B} \subseteq \mathrm{T}$ is the subset of random samples in the training set. The loss function L is chain decomposed with respect to the parameter θ as:

$$\frac{\partial L}{\partial \theta}(\theta, \pi; x, y) = \sum_{n\in \mathrm{N}} \frac{\partial L(\theta, \pi; x, y)}{\partial f_n(x;\theta)} \frac{\partial f_n(x;\theta)}{\partial \theta} \tag{9}$$

which depends on the gradient term of the decision tree is formulated as:

$$\frac{\partial L(\theta, \pi; x, y)}{\partial f_n(x;\theta)} = d_n(x;\theta) A_{n_r} - (1 - d_n(x;\theta)) A_{n_l} \tag{10}$$

Here n_l and n_r denote the left and right children of node n, respectively. For A_m, any node $m \in \mathrm{N}$ has the formula:

$$A_m = \frac{\sum_{\ell \in \mathrm{L}_m} \pi_{\ell_y} \mu_\ell(x \mid \theta)}{\mathrm{P}_T[y \mid x, \theta, \pi]} \tag{11}$$

where $\mathrm{L}_m \subseteq \mathrm{L}$ is the set of all leaf nodes with m as root node.

Now consider how to optimize π, i.e., minimize the empirical risk R, when θ is fixed:

$$\min_\pi R\left(\theta, \pi; \mathrm{T}\right) \tag{12}$$

This is a convex optimization problem and can be solved by the following equation:

$$\pi_{\ell_y}^{(t+1)} = \frac{1}{Z_\ell^{(t)}} \sum_{(x,y')\in \mathrm{T}} \frac{1_{y=y'} \pi_{\ell_{y'}}^{(t)} \mu_\ell(x \mid \theta)}{\mathrm{P}_T[y \mid x, \theta, \pi^{(t)}]} \tag{13}$$

where $\ell \in \mathrm{L}$, $y \in y$, and $Z_\ell^{(t)}$ are the normalization factors that ensure that $\sum_y \pi_{\ell_y}^{(t+1)} = 1$. The starting point $\pi_{\ell_y}^{(0)}$ is set to $|y|^{-1}$ in the iterative calculation.

II. C.Random Forest-based Mural Style Migration Modeling

Based on the theoretical framework of differentiable random forest, this section further applies it to the mural style migration task. Through the design of regularized optimization and multi-component loss function, a migration model that balances fidelity and artistry is constructed.

II. C. 1) Regularization Optimization

Path length regularization (PPL) is a regularization technique that is often used to control the complexity of neural network models. In deep neural networks, the high complexity of the model often leads to overfitting problems. To solve this problem, path length regularization effectively limits the complexity of the model and improves its generalization performance by restricting the information propagation paths in the neural network. Therefore, the regularization method is widely used in computer vision, natural language processing and other fields.

The basic idea of the method is to control the complexity of the model by limiting the length of the path from each neuron in the neural network to the output layer. Specifically, the method calculates the path lengths from each neuron to the output layer and weights the sum of these path lengths with a penalty term. This penalty term can be understood as a constraint on the model complexity, which can effectively avoid the occurrence of overfitting phenomenon.

The advantage is that it does not introduce additional hyperparameters compared to other regularization methods. This means that there is no need to manually adjust the hyperparameters when using the method, and the default parameters can be used directly. Moreover, the method is also relatively small in computation, which is suitable for large-scale deep neural networks. The formula is as follows:

$$L_{pl} = \sum\left[\frac{1}{\grave{o}^2} d\left(G_t\left(slerp\left(z_1, z_2\right)\right), G_{t+\grave{o}}\left(slerp\left(z_1, z_2\right)\right)\right)\right] \tag{14}$$

where $\grave{o}$ is the fine molecular segment, which can be regarded as the step size, and is generally replaced by e^{-4}, which is the intermediate hidden code obtained after mapping the network from the hidden-space random code, d denotes the perceptual distance, which is generally computed in the discriminator; t denotes a certain point in time, $t \in (0,1)$, and $t+\grave{o}$ denotes the next point in time; G is the generator; $slerp$ denotes linear interpolation, i.e., interpolation of the latent space according to the parameter t.

In the main loss function, the regularization term and the adversarial loss of the GAN network are inside one expression and can be optimized simultaneously. However, through training it can be observed that the regularization term is computed less frequently than the main loss function, so this chapter will optimize on the original regularization by evaluating the regularization term in a separate regularization process and letting it be executed every k training iterations.

Since the internal state of the Adam optimizer is shared between the loss term and the regularization term, this means that the optimizer will first process the gradient of the main loss, and after k iterations process the gradient of the regularization term once more. Therefore, this chapter is set to perform 16 iterations of the main loss function before performing one iteration of the regularization term to avoid overfitting.

II. C. 2) Loss function

Regularization optimization effectively suppresses model overfitting, but the quality of style migration still relies on the fine design of the loss function. This section combines the CycleGAN framework to ensure the content integrity and visual consistency of the style migration process through the synergy of the adversarial loss and the cyclic consistency loss.

An ordinary Generative Adversarial Network (GAN) consists of a generator and a discriminator; the generator wants to generate more realistic mural images, and the discriminator discriminates the authenticity of the generated images. The two compete with each other to achieve dynamic equilibrium.The loss function of GAN is described as follows:

$$\begin{aligned} L_{GAN}\left(f_{AB}, D_B, A, B\right) = E_{b\sim B}\left[\ln D_B(b)\right] \\ +E_{a\sim A}\left[\ln\left(1-D_B\left(f_{AB}(a)\right)\right)\right] \end{aligned} \tag{15}$$

where A and B denote the two domains of mural images whose styles are ported, L_{GAN} is the loss value between the measured image and the image, f_{AB} is the mapping function from domain A to domain B, and D_B is the discriminator. $E_{b\sim B}$ denotes the probability that b belongs to the defined domain B and the expected value of b over B. $E_{a\sim A}$ denotes the probability that a belongs to the domain of definition A and the expected value of a over A. $\ln$ is the natural logarithm of the result, and the purpose of the discriminator D_B is to distinguish between the mural B in the region B and the fake mural $f_{AB}(a)$ generated by the generator, so that the value of the first term $D_B(b)$ converges to 1. So that the value of the second term $D_B\left(f_{AB}(a)\right)$ converges to 0.

The task CycleGAN needs to accomplish is to migrate the mural color style in domain A to B. Using two GANs to realize asymmetric training of data requires not only calculating the loss function of two GANs, but also defining a loss function to reflect the activity of the whole network. To ensure the stability of the recurrent network, the concept of recurrent consistency is therefore introduced to set the corresponding recurrent consistency loss function.

$$\begin{aligned} L_{cyc}\left(f_{AB}, f_{BA}\right) = E_{a\sim A}\left[\left\|f_{BA}\left(f_{AB}(a)\right)-a\right\|_1\right] \\ +E_{b\sim B}\left[\left\|f_{AB}\left(f_{BA}(b)\right)-b\right\|_1\right] \end{aligned} \tag{16}$$

In the above equation (16), a is the mural image in color domain and b is the mural image in black and white domain. f_{AB} is the generator that converts the input image to the color domain and f_{BA} is the generator that converts the image to the black and white part. $E_{b\sim B}$ denotes the probability that b belongs to the defined domain B and the expectation of b over B. $E_{a\sim A}$ denotes the probability that a belongs to the definitional domain A and the expected value of a over A. This loss function is the loss consistency function of CycleGAN.

Because there are two generators and two discriminators in the Cycle Generative Adversarial Network therefore $L_{GAN}\left(f_{AB}, D_B, A, B\right)$, $L_{GAN}\left(f_{BA}, D_A, B, A\right)$ and $L_{cyc}\left(f_{AB}, f_{BA}\right)$ are summed to obtain the loss function of the recurrent generative adversarial network.

$$L_{full}\left(f_{AB},f_{BA},D_A,D_B\right)=L_{GAN}\left(f_{AB},D_B,A,B\right) +L_{GAN}\left(f_{BA},D_A,B,A\right)+\lambda L_{cyc}\left(f_{AB},f_{BA}\right) \tag{17}$$

CycleGAN's loss function consists of several components, each optimized for a different aspect of the model. The cyclic consistency loss ensures that the source domain image remains consistent with the original image after two conversions (first to the target domain and then back to the source domain), thus preserving the key content of the original image. This loss function plays a key role in the experiments by enabling CycleGAN to transform styles without destroying the basic structure and information of the image. The adversarial loss, on the other hand, guides the generator to produce a more realistic image of the target domain through a discriminator.

III. Experimental Validation and Effectiveness Assessment of Random Forest-Driven Mural Style Migration Modeling

By constructing a micro-random forest-driven mural style migration model, this paper solves the problem of color distortion and style adaptation in Chapter II. In order to verify the practical effectiveness of the model in cultural and tourism integration scenarios, Chapter 3 will focus on experimental design and multi-dimensional effect evaluation, combining quantitative indicators and user feedback to systematically analyze the innovation and practicality of the algorithm.

III. A. Experimental setup

We conducted detailed experiments on the dataset constructed in this paper based on the Random Forest algorithm CycleGAN, which is first compared and analyzed in detail with high-performance style migration algorithms at the current stage, and then verified the validity of the various parts proposed in this study through ablation experiments.

III. A. 1) Experimental setup and data set

The experiments in this chapter were conducted on the collected BHC mural dataset, which was randomly divided into a training set and a test set in a ratio of 9:1.

Throughout the training phase, we initialized the weights of all networks to a Gaussian distribution with mean 0 and standard deviation 0.02. We trained our networks 200 times using the Adam optimizer with parameters B of 0.5 and Bβ2 of 0.999, where the learning rate was 0.0002 and linear decay started after 100 epochs.

All experiments in this chapter are conducted on a computer operating on Ubuntu 14.04.1. The specific experiment ring is using inter(R)Core(TM)i7-5930K CPU@3.50GHz CPU, CUDA 10.0.130, and Python version 3.7.0.

III. A. 2) Evaluation indicators

In order to fully evaluate the effectiveness of the algorithm, we use quantitative metrics and user survey scores for comparative evaluation with state-of-the-art image style migration algorithms.

Quantitative Metrics: For quantitative metrics evaluation, this chapter uses existing work commonly used for image generation quality assessment

(1) FID: FID calculates the distance between two image domains at the feature level, and evaluates the similarity between the real data and the generated data by calculating the mean and covariance matrices of the features extracted by the pre-trained Inception V31691 network.The smaller the value of FID is, the more similar the two sets of data are evaluated, which, in this chapter, indicates that the mural style of the generated image is more effective, the detailed The calculation formula is shown in equation (18).

$$FID(x,g)=\left\|\mu_x-\mu_g\right\|^2+Tr\left(\sum{}_x+\sum{}_g-2\sqrt{\sum{}_x\sum{}_g}\right) \tag{18}$$

where x is the real image, g is the corresponding generated image, and μ, Z and Tr denote the mean, covariance and inter of the features, respectively.

(2) KID:KID is computed in a similar way to FID, but evaluates the similarity between real and generated data by calculating the squared value of the maximum mean difference between features obtained by the InceptionV3 network. In contrast to FID, which relies on empirical bias, KID employs an unbiased estimate of the cubic kernel that more closely matches human perceptual abilities.The smaller the values of the KID mean and variance, the better the effect of the generated mural style. The detailed calculation formula is shown in equation (19).

$$KID(x,g)=\frac{1}{m(m-1)}\sum_{i\neq j}^{m}k\left(x_i,x_j\right)+\frac{1}{n(n-1)}\sum_{i\neq j}^{m}k\left(g_i,g_j\right) \tag{19}$$

where m is the number of samples of the real image x, n is the number of samples corresponding to the generated image g, and k is a polynomial kernel function.

User Survey Ratings: Due to the large personal aesthetic subjectivity in the evaluation of artworks, conducting user rating surveys that reflect subjective evaluations to evaluate the generated mural style images can provide a more comprehensive assessment of the effectiveness of the algorithms. Specifically, we developed a Python-based rating website that displays mural style images generated by different algorithms, which were randomly selected from a test set. Participants were asked to rate the mural style images generated by the different algorithms on a scale of 1 to 5 based on their visual appeal, with 5 being the most appealing.

III. A. 3) Comparison of methods

In order to validate the stylistic effect of generating mural images and the effectiveness of our method, we compare our method with state-of-the-art CNN-based and GAN-based style migration methods based on the DHST dataset in qualitative and quantitative experiments, specifically Gatys, AesUST, CycleGAN, ChipGAN, CUT, LseSim, QS-Attn and the random forest-based style migration algorithm for mural art proposed in this paper. Among them, Gatys and AesUST are style migration algorithms based on instance images, CycleGAN is an image transformation method based on cyclic consistency structure, ChipGAN is -an advanced style migration algorithm for fresco art, which is improved on the basis of CycleGAN model, and CUT, LseSim and QS-Attn are all contrast learning based image transformation methods.

III. B. Comparison of the effects of multidimensional style migration

III. B. 1) Quantitative comparison

We use the FID and KID evaluation metrics, which are widely used in image generation, for further quantitative comparison. The quantitative comparison results of the comparison experiments are shown in Fig. 2 (where the last item is the quantitative comparison between the training set and the test set in the BHC mural dataset to illustrate the validity and reliability of this evaluation metric), and it can be found that our method obtains the best results among all evaluation metrics relative to the other methods, which suggests that our method is able to generate more realistic mural art style compared to the other methods for the Images.

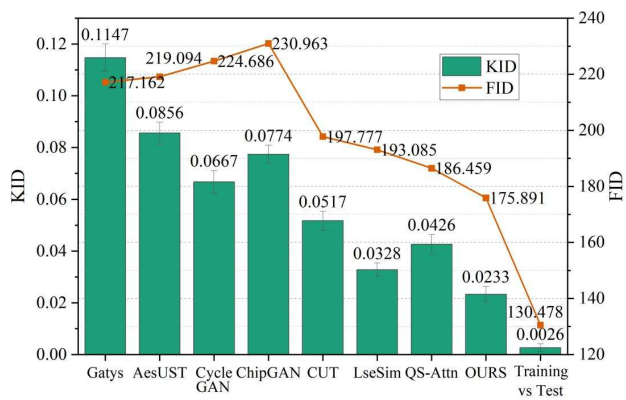

Figure 2: Quantitative comparison of FID and KID indicators by different methods

The RF-CycleGAN model proposed in this paper significantly outperforms other comparative algorithms in both FID of 175.891 and KID of 0.0233 metrics, indicating that the style of the generated images is closest to the real mural data distribution. Especially in the comparison with the mural-specific algorithm ChipGAN with FID of 230.963, the FID value of RF-CycleGAN is reduced by about 23.8%, which verifies the advantage of the Random Forest algorithm in the modeling of complex color mapping relationships. In addition, the FID difference between the training set and the test set (130.478 vs. 175.891) indicates that the model does not suffer from serious overfitting and has a strong generalization ability.

III. B. 2) User rating surveys

To further demonstrate the effectiveness of the RF-CycleGAN method in this paper, we conducted a user evaluation survey study to compare our method with other style migration methods. In this study, participants are presented with a web page containing several stylized images of mural art generated by different methods, which are randomly selected from each test set. Participants were asked to rate the given stylized images of frescoes on a scale of 1 to 5 based on visual appeal, with 5 being the most appealing. A total of 1,248 votes were collected from 220 different participants (participants were concentrated in the age range of 20 to 30 years old, from both art professional and non-art professional backgrounds). The results of the user evaluation survey study scores are shown in Figure 3.

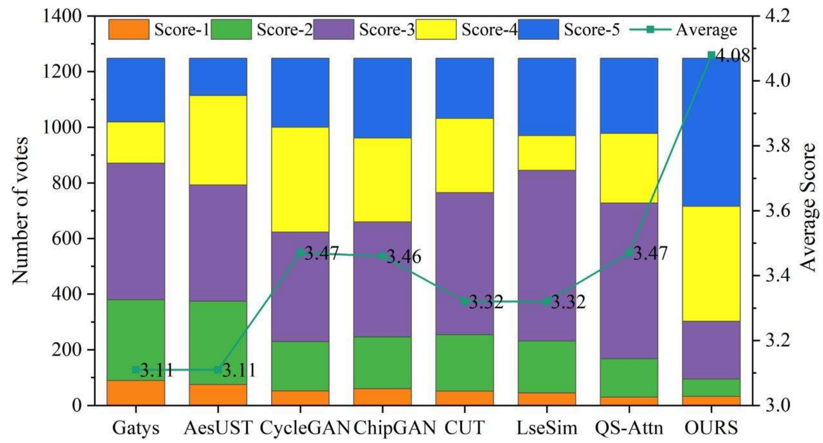

Figure 3: User evaluation survey research score results

The results of the user survey show that the average visual attractiveness of the images generated by RF-CycleGAN reaches 4.08, which is much higher than that of CycleGAN's 3.47 and CUT's 3.32. Specifically, 42.6% of the votes are “5 out of 5”, compared with only 19.9% of the votes of traditional CycleGAN, which indicates that the model incorporating Random Forest can better balance the stylistic art and content fidelity to meet the public aesthetic demand. The model incorporating Random Forest can better balance the style artistry and content fidelity, which is in line with the public aesthetic demand.

III. C. Ablation experiments

To further parse the contribution of each module of the model to the effect of style migration, this section verifies the validity of key loss functions (e.g., color contrast loss, semantic loss) through ablation experiments to ensure the reliability of the model in the retention of fresco art features.

Our model consists of four key loss constraint modules, namely, content-based contrast loss for overcoming the effects of inter-domain stylistic differences, line loss for learning fresco line-drawing shapes, color contrast loss and color-facilitated antagonistic loss for learning fresco recoloring styles, and semantic loss for improving the visual quality of content element regions in parts of the generated image. In order to validate the effectiveness of each loss constraint module in our method, this subsection conducts ablation research experiments on the key loss components of our method.

Using the same experimental setup, we trained three variant network models which remove the key loss constraint modules on top of the RF-CycleGAN model respectively, namely variant model 1 which removes the content-based contrast loss on top of the original model, variant model 2 which removes the semantic loss, and variant model 3 which removes the correlation loss of the line and color styles facilitation.

To further validate the effectiveness of the proposed module with the loss associated with the facilitated model for learning color features, we trained a separate variant network model to compare with RF-CycleGAN, which removes the color contrast loss as well as the adversarial loss of color facilitation on the basis of the RF-CycleGAN model. We extracted the primary colors of the stylized images generated by different models and the real mural data in the BHC dataset respectively, and then compared the distribution of the primary colors of each data, so as to achieve the assessment of the color fidelity of the stylized images generated by different models, in order to validate the effectiveness of our method. Specifically, we use k-means clustering algorithm to extract the clustered primary colors for each image, and then use a streaming data downscaling tool UMAP to downscale the extracted clustered primary colors and map them into the 3D space for visualization. The UMAP visualization results corresponding to the image clustering primary colors of different datasets are shown in Fig. 4, which includes the image clustering primary color visualization results of three datasets.

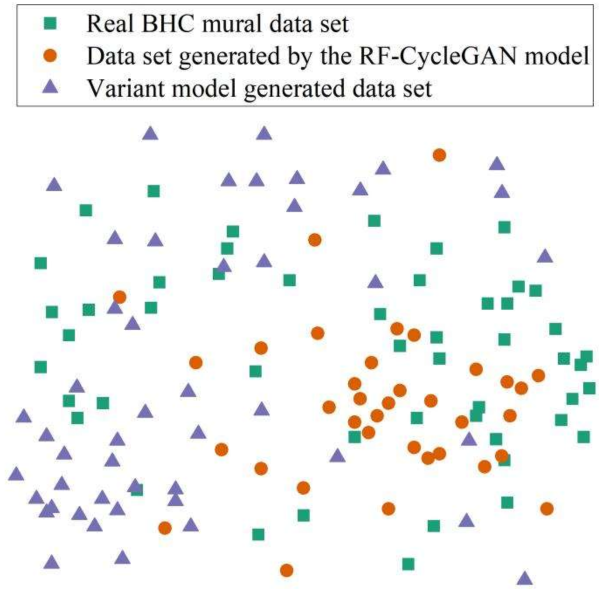

Figure 4: UMAP visualization results of the main color of image clustering

From the figure, it can be found that the color distribution of the image dataset generated by RF-CycleGAN is closer to the color distribution of the real mural image dataset than that of the image dataset generated by the variant network model, which indicates that our method is able to generate images with more realistic color style characteristics of the mural paintings, proving the effectiveness of our method. Through the above comparative analysis, it can be seen that the content-based contrast loss proposed in this paper can effectively overcome the negative impact caused by inter-domain style differences and improve the quality of the generated images; the proposed semantic loss can effectively constrain the relevant regions in the mural image dataset that lack content elements to carry out unwanted style migrations, and improve the visual quality of the corresponding regions; the proposed line loss, color contrast loss, and color-facilitated confrontation loss can constrain the model to learn realistic fresco line drawing shapes and heavy color stylistic features to generate more realistic fresco artworks.

III. D. Expert assessment

In order to verify whether the effect after style migration based on random forest algorithm proposed in this paper reaches the goal, 20 experts about the field of frescoes were selected to help make a questionnaire about the effect of style migration of frescoes images, which were scored from the three aspects of the appearance of the generated images in terms of the ornamental, the satisfaction of the style simulation effect, and the extent of the presentation of frescoes' inner meaning, with the scores as an integer from 1 to 5, with 1 being unsatisfied, 5 being very satisfied, and the middle is progressive step by step. Regarding the image appearance, style simulation and connotation conveyance evaluation results of the images generated by the randomized algorithm-based mural style migration model in this paper are shown in Fig. 5, Fig. 6 and Fig. 7, respectively.

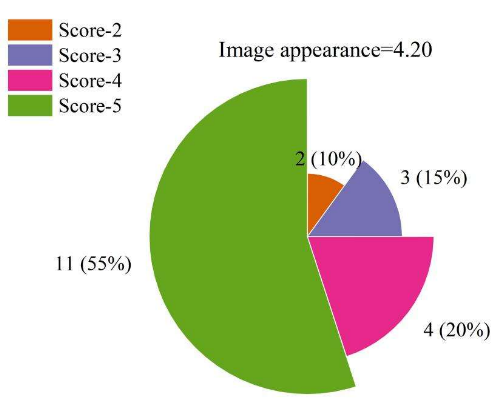

Figure 5: The image appearance evaluation result of the generated image

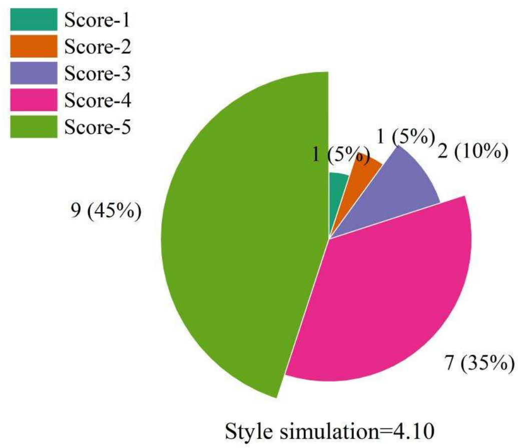

Figure 6: The style simulation evaluation results of the generated images

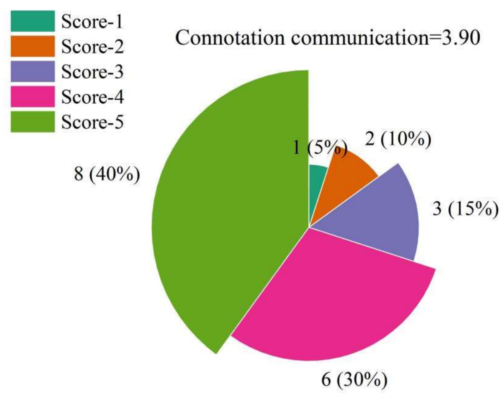

Figure 7: The connotation of the generated image conveys the assessment results

For the evaluation of cultural heritage protection experts, the generated images obtained average scores of 4.20 and 4.10 in the dimensions of “Image Appearance” and “Style Simulation” respectively, and there is no “Score 1” evaluation in Image Appearance. There is no “Score 1” in image appearance, which indicates that the model achieves professional recognition in the reduction of the artistic features of the mural. However, the score of “Connotation Conveyance” is slightly lower, 3.90, and some experts point out that some generated images do not express enough symbolic elements of the historical background of the frescoes, and that semantic constraints need to be further integrated in the future to enhance the depth of cultural connotation conveyance.

IV. Research and application of cultural and creative product design based on the migration of fresco image styles

It is experimentally verified that the style migration model based on random forest excels in both artistry and fidelity of mural images. Based on this, Chapter 4 will explore the practical application of the style migration results in the scenario of cultural and tourism integration, and realize the living dissemination of cultural heritage through cultural and creative product design.

Art derivatives are a series of practical products with a sense of artistic symbols. Derivative design using mural images after style migration is a redesign of national symbols. This chapter will take the visual image design of mural images as an example, and apply the migrated mural images to the overall visual image design of mural paintings. The main contents of this chapter are: pre-issuance of questionnaire research, confirmation of design strategy based on the results, and final output of visual design ideas.

IV. A. Design Research

IV. A. 1) Basic User Information of Research Subjects

A total of 186 people filled out this research, of which male students accounted for 48.92%, totaling 91 people; 95 female students, accounting for 51.07%. In order to ensure the extent of coverage of the questionnaire research, this questionnaire also from the age, industry, education and other aspects of the research, the results show that in the 186 people in the 26-30 year old group is the most, accounting for 39.78%, 18-25 year old group is the second, accounting for 31.18%, each age group is involved; in the research object, the university bachelor's degree of 81 people, accounting for 43.55%, and more than 10.75% are graduate students and above. In the results of their study/engaged in the industry results can be learned, the industry of the research object is widely distributed, different concepts of the crowd treat the same thing with different attitudes, making the results of this research more comprehensive and thoughtful.

IV. A. 2) The public's awareness of the visual image of tourism brands

First of all, we investigated the extent to which the public believes that the visual image design of tourism brand plays a role in improving local awareness, promoting local culture and deepening the public's impression of the region, and the role of the visual image of tourism brand is shown in Figure 8.

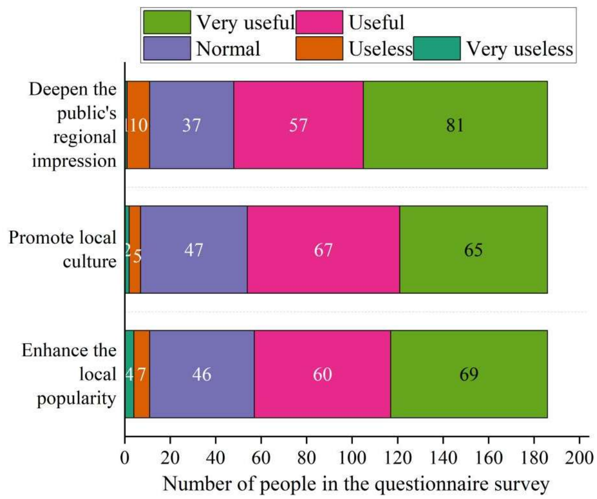

Figure 8: The role of the visual image of tourism brands

According to the results, 69.35% of the respondents believe that good brand visual identity design can effectively improve local awareness; In the survey on whether the brand visual image can effectively promote local culture, 36.95% of people chose the "very effective" option, indicating their recognition of its role; In terms of deepening the image of the public, 30.65% thought it had a role, 43.55% thought it was very effective, and 5.38% thought it had no effect. Overall, the public retains a positive attitude towards the role of the visual image of tourism brands.

IV. A. 3) Research on cultural and creative products for tourism brand image design

Figure 9 shows the results of the research on the statistics of the reasons for not buying cultural and creative products designed with the image of the tourism brand.

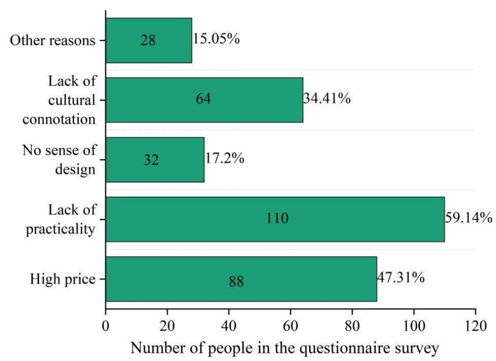

Figure 9: The reasons for not buying cultural and creative products

Among them, 47.31% think that the price of the cultural and creative products is too high, 59.14% think that the cultural and creative products are not practical, 34.41% think that most of the products lack cultural connotations, and 17.20% think that the products are not enough to have a sense of design.

In the survey of people who have purchased cultural and creative products for their satisfaction with the products they bought, it was found that most people are still satisfied, and the satisfaction of buying cultural and creative products of tourism brand image design is shown in Figure 10.

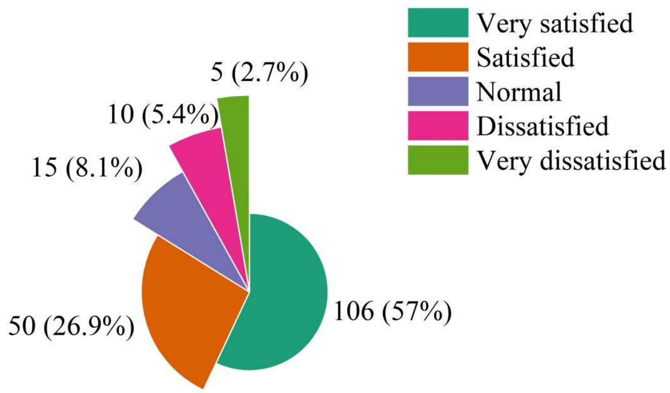

Figure 10: A satisfaction survey on the purchased cultural and creative products

For the purchased cultural and creative products of tourism brand image design, 57% of the customers said they were very satisfied, 26.9% said they were satisfied, and those who were dissatisfied and very dissatisfied only accounted for 8.1%, indicating that the customers' satisfaction with the cultural and creative products of the mural style relocation is still high.

IV. B. Design Ideas for Cultural and Creative Products

Based on the previous research on cultural and creative product design, this section proposes a design strategy that integrates the advantages of algorithms and market demand, and builds a technology-driven cultural and creative development path from the three aspects of cultural symbols, visual styling, and color system.

IV. B. 1) Refinement of cultural factors

Based on the high-fidelity restoration of historical details by the mural style migration model proposed in the previous section, the design needs to deeply excavate the cultural symbols and spiritual connotations behind the mural paintings. Firstly, the core narrative elements of the mural paintings are extracted by semantic segmentation technology, focusing on strengthening the symbols with symbolic meanings, such as the flying sky pattern, the lotus seat, and the clothing of the feeders. Second, the stylized images generated by the model are used to construct a cultural symbol library, and the high-frequency visual elements are identified by a random forest-driven feature clustering algorithm, so as to filter out the cultural symbols with both artistic value and public recognition.

IV. B. 2) Refinement of phenomenal elements

Relying on the improved line loss function and content fidelity mechanism in the style migration model, the modeling features of the fresco images are structurally extracted. First, the edge detection algorithm is used to extract the outline of the fresco line drawing, and the stability advantage of the path length regularization constraints in the generated image is combined to retain the unique “iron line drawing” brushstroke style of the fresco. Secondly, based on the high rating of “visual attractiveness” in the user survey, fresco composition rules are integrated into the product design. For example, the radioactive structure of the Mogao Grottoes Zaojing pattern is transformed into the design of tea sets, or the dynamic curves of the “S-shaped” figures in the frescoes are applied to the silk scarf pattern, realizing the organic fusion of traditional aesthetics and modern design.

IV. B. 3) Color element refinement

Combining the color contrast loss and microscopic random forest color correction techniques proposed in this paper, a scientific mural painting color application system is constructed. First of all, based on the primary color distribution of the image generated by the style migration model, the typical traditional color system is extracted, such as the combination of the three primary colors of Dunhuang mural paintings, namely, vermillion red, stone green, and earth yellow, and the modern aesthetic preferences are adapted through the hue saturation optimization module. Referring to the users' demand for cultural connotations in the user research, we establish the color semantic mapping rules: warm tones correspond to a sense of historical heaviness, which is applied to antique crafts; cold tones convey a peaceful mood, which is applicable to home textiles.

V. Conclusion

In this study, we constructed a fresco style migration model by combining the differentiable Random Forest algorithm with the CycleGAN framework, effectively solved the color distortion problem, and verified its superiority in experiments. Quantitative evaluation shows that the FID value of RF-CycleGAN is 23.8% lower than that of ChipGAN, a mural-specific algorithm (175.891 and 230.963), and the KID value is only 0.0233, indicating that the generated image styles are highly close to the real mural distribution. In the user survey, 42.6% of the participants rated the generated images as "5 out of 5", and both art professionals and non-professionals recognized their visual appeal, with an average score of 4.08. The expert evaluation further showed that the model scored 4.20 and 4.10 in the dimensions of "image appearance" and "style simulation", respectively, but the score of "connotation communication" was slightly lower, at 3.90, indicating that semantic constraints should be strengthened to improve cultural depth. Based on the results of the model, a cultural and creative design path integrating the core symbols of murals, line shapes and color systems is proposed. Combined with the user research data, 57% of the users are "very satisfied" with the existing cultural and creative products, which provides technical support for the dissemination of cultural heritage under the scenario of cultural and tourism integration.

References

[1] Guo, Y. (2025). Enhancing DVNN-WCSM Technique for Double-Valued Neutrosophic Multiple-Attribute Decision-Making in Digital Economy: A Case Study on Enhancing the Quality of Development of Henan's Cultural and Tourism Industry. Neutrosophic Sets and Systems, vol. 75/2025: An International Journal in Information Science and Engineering, 49, 390.

[2] Tang, C., Liu, Y., Wan, Z., & Liang, W. (2023). Evaluation system and influencing paths for the integration of culture and tourism in traditional villages. Journal of Geographical Sciences, 33(12), 2489-2510.

[3] Wang, J., & Hu, X. (2025). High-Quality Development Evaluation of Cultural and Tourism Integration Empowered by the Digital Economy under Double Valued Neutrosophic Sets. Neutrosophic Sets and Systems, 81, 145-158.

[4] Hao, B. (2025). Research on the Integration of Culture and Tourism Development Strategies for Liaoning's Night Economy Enabled by E-Commerce. Highlights in Business, Economics and Management, 49, 158-165.

[5] Zeng, M., Shen, S., & Gu, J. (2023). How does the integration of cultural and tourism industries impact the value added to tourism value chain: Evidences from Jiangsu Province of China. Plos one, 18(6), e0287610.

[6] Jiang, T., Xu, Y., Li, Y., & Xia, Y. (2025). Integration of public libraries and cultural tourism in China: An analysis of library attractiveness components based on tourist review mining. Information Processing & Management, 62(2), 104000.

[7] Katsoni, V., Upadhya, A., & Stratigea, A. (2017). Tourism, culture and heritage in a smart economy. Springer proceedings in business and economics.

[8] Ayaz, N., & Şamata, N. (2017). Integration of congress tourism to the cultural tourism destinations as an economic product. Journal of Tourism and Hospitality Management, 5(1), 53-61.

[9] Jovicic, D. (2016). Cultural tourism in the context of relations between mass and alternative tourism. Current Issues in Tourism, 19(6), 605-612.

[10] Li, W. U., Hao, L., Huajun, Y. U., & Rongmian, H. U. O. (2021). Spatial differentiation and driving factors of the integrated development of culture and tourism in China. Economic geography, 41(2), 214-221.

[11] Sarifudin, A., Jazuli, M., & Syarif, M. I. (2022, October). The Existence of Murals in Supporting the Aesthetics of Tourism Villages. In Proceedings of International Conference on Science, Education, and Technology (Vol. 8, pp. 599-606).

[12] Stephen, T. (2016). Street murals as a unique tangible cultural heritage: a case study of artifact value preservation'. Int J Cult Creat Ind, 4(1), 48-61.

[13] Wen, D. (2024). Analysis of Human Figures, Artistic Value and Enlightenment to Folk Photography in Dunhuang Murals. Mediterranean Archaeology and Archaeometry, 24(3), 300-313.

[14] Wang, X., Song, N., Zhang, L., & Jiang, Y. (2018). Understanding subjects contained in Dunhuang mural images for deep semantic annotation. Journal of documentation, 74(2), 333-353.

[15] Sun, Z., Zhao, D., & Zhang, H. (2022). The innovative application of Dunhuang murals patterns in cultural creation design. Journal of Education, Humanities and Social Sciences, 5, 149-162.

[16] Kwon, G., & Ye, J. C. (2022). Clipstyler: Image style transfer with a single text condition. In Proceedings of the IEEE/CVF conference on computer vision and pattern recognition (pp. 18062-18071).

[17] Moore, I. (2014). Cultural and Creative Industries concept–a historical perspective. Procedia-Social and Behavioral Sciences, 110, 738-746.

[18] Zheng, J., & Chan, R. (2014). The impact of 'creative industry clusters' on cultural and creative industry development in Shanghai. City, Culture and Society, 5(1), 9-22.

[19] Fillis, I., & Lehman, K. (2022). Cultural murals and the evolving nature of the hero concept: an arts marketing context. Arts and the Market, 12(3), 197-214.

[20] Lu, X., Yang, Y., Wang, L., & Wang, H. (2022). Cultural and creative design of Dunhuang murals in Xixia period based on deep learning. Wireless Communications and Mobile Computing, 2022(1), 7161593.

[21] Netwong, T., Khrouthongkhieo, N., & Pijitkamnerd, B. (2024). Creative Products Based on Local Wisdom Derived from Mural Paintings of Suphan Buri Province, Thailand. Harmonia: Journal of Arts Research and Education, 24(2), 401-410.

[22] De-Miguel-Molina, B., & De-Miguel-Molina, M. (2021). Conclusions. The Sustainability of Cultural and Creative Mural Spaces. Cultural and Creative Mural Spaces: Community, Culture and Tourism of Uruguayan Contemporary Muralism and Other International Mural Spaces, 209-211.