International Journal for Housing Science and Its Applications
Publish August 10, 2025. Volume 46, Issue 4 Pages 5255-5263

https://doi.org/10.70517/ijhsa464365

A Study on the Visual Expression of Cultural Identity in Contemporary Oil Painting Creation

Yan Gao[1,*] and Fengtao Yang[2,*]
[1] Jiangsu Vocational College Of Electronics and Information, Huaian, Jiangsu, 223301, China
[2] Huaian Senior Vocational & Technical School, Huaian, Jiangsu, 223001, China
Corresponding authors: (e-mail: gaoyanhuashi2004@163.com).

Abstract The application of artificial intelligence in the field of art is becoming more and more widespread, especially in style transformation and art generation shows great potential. As an important form of artistic expression, traditional oil painting carries profound cultural connotation and aesthetic value. Aiming at the problems of unstable generation quality and insufficient texture feature extraction in traditional oil painting style migration, this study proposes an oil painting style migration method based on improved CycleGAN. The method adopts the relativistic discriminator and PatchGAN structure by introducing texture features as a priori knowledge input to the generator, and optimizes the loss function design. Experimental validation is carried out on a dataset containing 5000 images, and the Adam optimizer is used for 300 rounds of training. The experimental results show that the method outperforms existing methods in two evaluation indexes, structural similarity index (SSIM) and peak signal-to-noise ratio (PSNR), where the SSIM value reaches 0.738 in Landscape→Oil style migration, which is an improvement of 0.127 compared to the GAN method. 800 oil paintings generated are evaluated, and the average score of the automatic evaluation is 4.236 points, and the average score of manual evaluation is 4.281 points. The texture characterization shows that different types of oil paintings present significant differences in indicators such as roughness and contrast. The study shows that the method effectively improves the quality and realism of oil painting style migration and provides a new technical support for digital art creation.

Index Terms Oil painting style migration, CycleGAN, texture features, structural similarity index, peak signal-to-noise ratio, digital art creation

I. Introduction

As an important branch of art, oil painting itself has a long history and deep traditional culture, and also contains many propositions closely related to nature and human beings [1]. Many oil painting artists have a keen artistic insight and a strong sense of social responsibility, they not only pursue formal aesthetics, but also express their own thinking about cultural identity and identity, so that oil paintings are not only infected with the heart from the color and composition of these characteristics of painting, to give a stronger artistic expression, but also from the humanistic feelings, social emotions shocked the viewer's mind, awakening the viewer's social consciousness [2]-[5].

Oil painting is the external manifestation of cultural identity, each nation and each country has its own unique culture, including language, religion, folklore, history and other elements, which constitute the cultural identity of a nation [6]-[8]. By perceiving and understanding the cultural environment in which they live, painters integrate the essence of the culture into their works, thus showing their interpretation of cultural identity [9], [10]. Famous artworks and artworks in the world often contain the artist's love and identification with the culture to which they belong [11]. For example, by painting landscapes, flowers and birds, painters in ancient China showed the world the landscape mood and traditional aesthetics of Chinese culture [12], [13]. Oil painting is not only an expression of cultural identity, but also an exploration and affirmation of one's own identity [14]. In oil painting, artists integrate their inner world with the cultural environment they live in, and express their thoughts about life and the world through their works, and the integration of cultural identity will directly affect the artistic performance of the works [15]-[17].

This study proposes an improved cycle-consistent adversarial network method to solve the key technical problems in oil painting style migration. First, by deeply analyzing the visual characteristics of oil painting art, texture information is extracted as a priori knowledge to be introduced into the generator network, which enhances the model's ability to learn the unique texture of oil paintings. Second, the relativistic discriminator is used to replace the traditional discriminator, which is combined with the PatchGAN structure to enhance the quality of local details in the generated images. In terms of loss function design, L2 loss is introduced as an antagonistic loss, and the average relativistic discriminator loss is used to optimize the training process. Through these technical improvements, it is expected to realize higher quality oil painting style migration effect and provide effective technical support for digital art creation.

II. Cultural identity and artistic expression in the creation of oil paintings

II. A. Principles of GAN and model architecture

The recurrent consistency adversarial network used for the experiments in this paper is from the GAN network [18], and the advantage of this style migration method is that it can realize the migration of an image to the target style domain without having to train on two one-to-one datasets. Generative Adversarial Network is composed of two parts, a generator network G and a discriminator network D, where G is used to generate sample images and D is used to distinguish between the real image and the generated image, the GAN training process is actually the two neural networks deceiving each other and optimizing each other in the generative discriminative game against each other with only a simple loss function can make the two reach a balance, Figure 1 shows the network structure of GAN.

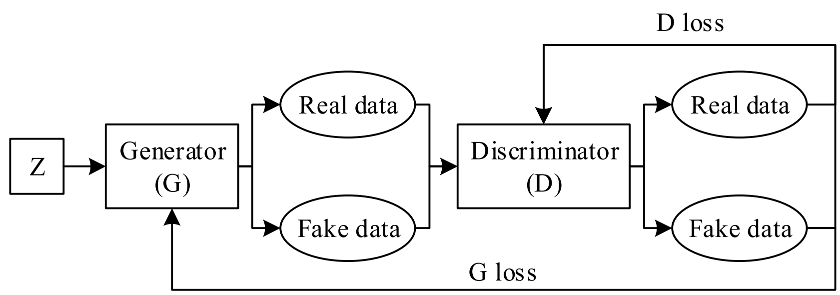


Figure 1: Standard gan structure

In the process of the game between the generator and the discriminator, G continuously learns and improves the ability to create fake images, D gradually improves the ability to judge the true and false pictures, G and D continuously play the game of cheating each other during the training process to finally reach a balance, the objective function expression is as follows:

$$\min_G \max_D V(D,G) = \mathrm{E}_{x\sim P_{data}(x)}[\log D(x)] + \mathrm{E}_{z\sim P_z(z)}[\log(1-D(G(z)))] \tag{1}$$

In the training process, we found that GAN is unstable and training does not converge, the model is easy to collapse, although the generative adversarial network of the oil painting style migration effect is better than CGAN, but a major disadvantage is that the coloring effect is not very satisfactory, so that is the reason why this paper's experiments to introduce the cyclic consistency adversarial network.

II. B. Improved CycleCAN-based generator

Generator is the most important part of GAN, the final result of GAN is to get a well-trained generator and use it to generate various images, and the merit of the loss function in the process of training the generator is the deciding factor of the final result. Therefore, this section improves the CycleGAN style migration model through the perspective of generator and generation against loss function [19].

The idea of CycleGAN is mainly derived from real-life language translation problems, and adopts a cyclic structure to constrain the generator without any changes in the network structure and operation principle of individual GANs. This chapter mainly improves the CycleGAN model from the perspectives of generator and loss function, inspired by cGAN, by extracting the more obvious texture features of traditional oil painting drawing features as a priori knowledge input to the generator. This chapter uses the image generated by the original CycleGAN model as a reference comparison object to analyze the feasibility and advantages of the method in this paper.

II. B. 1) Improvement of the generator

The generator of CycleGAN consists of residual network, the advantages of residual network are easy to extract features, easy to train, it is an extremely widely used neural network. The main steps are to first downsample the image, then change the image features by transforming the network, and finally restore the complete image back by upsampling.The specific structure of CycleGAN contains two downsampled convolutional layers with a step size of 2, nine residual modules, and two upsampled convolutional layers with a step size of 1/2. In order to input texture features to the generator as additional conditions, the input to the generator needs to be changed to four channels, while the output remains the same at three channels.

II. B. 2) Generating the Adversarial Loss Function

In this way, this section modifies the discriminator to a relativistic discriminator and also modifies the loss function. The discriminator model is adopted from PatchGAN [20] used in the original method, which is, in short, a rather novel and powerful discriminator that cleverly designs the inputs as matrices of $n \times n$. Compared to the original discriminator that outputs only one piece of data, this method effectively improves the quality of the generated oil painting images.

In this chapter, the L2 loss will be used as the counter loss and the average relativistic discriminator loss will be used. The modified discriminator loss and the adversarial loss are as follows:

$$\begin{aligned} L_D = {} & \mathrm{E}_{x \sim P_{data}(x)}\left[\left(D(X) - \mathrm{E}_{y \sim P_{data}(y)}[D(G(Y))] - 1\right)^2\right] \\ & + \mathrm{E}_{y \sim P_{data}(y)}\left[\left(D(G(Y)) - \mathrm{E}_{x \sim P_{data}(x)}[D(X)] + 1\right)^2\right] \end{aligned} \tag{2}$$

$$\begin{aligned} L_{GAN}\left(G, D_Y, X, Y\right) = {} & \mathrm{E}_{y \sim P_{data}(y)}\left[\left(D_Y(G(Y)) - \mathrm{E}_{x \sim P_{data}(x)}[D_Y(X)] - 1\right)^2\right] \\ & + \mathrm{E}_{x \sim P_{data}(x)}\left[\left(D_Y(X) - \mathrm{E}_{y \sim P_{data}(y)}[D_Y(G(Y))] + 1\right)^2\right] \end{aligned} \tag{3}$$

L_{cyc} and L_{idt} are not changed, so the total loss of the model is shown in equation (4).

$$\begin{aligned} & L_{GAN}(G, F, D_X, D_Y) = L_{GAN}(G, D_Y, X, Y) \\ & + L_{GAN}(F, D_X, X, Y) + \lambda_1 L_{cyc}(G, F) + \lambda_2 L_{idt}(G, F) \end{aligned} \tag{4}$$

300 epoches were trained following the same training settings as CycleGAN.

II. C.Oil painting generation algorithm

Receive the source image in real time and evaluate the nature of the image, i.e., color image vs. grayscale map, convert to grayscale map if color image and take sample points if grayscale map.

Color image is converted to grayscale map, i.e.:

$$Q_1 = 0.30 * R + 0.59 * G + 0.12 * B \tag{5}$$

Q_1 represents the grayscale value of a grayscale map pixel point; R, G, and B represent the red, green, and blue channel color values of a color image pixel point.

$$\begin{aligned} & Q_2 = \frac{30 * R + 150 * G + 77 * B + 255}{256} \\ & Q_2 = \left(30 * R + 150 * G + 77 * B + 255\right) >> 8 \end{aligned} \tag{6}$$

Q_2 represents the grayscale value of the pixel point of the grayscale map; R, G, B represent the color value of the red, green, and blue channels of the pixel point of the color image, and $>> 8$ represents the shift to the right by 8 bits.

Raster based approach oriented grayscale map to obtain sample points with random offset. The grayscale map is divided into multiple rasters, each raster contains $7 * 7$ pixels; the vertices of each raster are the sampling points; a random value is generated in the range of 1-3, and the sampling points are shifted by 3 times the random value in the horizontal position, and by a random value in the vertical position. Horizontal position offset and vertical position offset calculation formula that is:

$$Offset\_x = 3 * [Rand()\%3] \tag{7}$$

$$Offset\_y = Rand()\%3 \tag{8}$$

$offset\_x$ represents the horizontal position offset; $offset\_y$ represents the vertical position offset; $Rand()\%3$ represents the remainder of the random variable divided by 3, i.e., a random value in the range $1-3$.

The horizontal and vertical position offsets are added for the horizontal and vertical positions of the sampled points.

Using the grayscale value of the sampled point as a carrier, the horizontal and vertical edge operators are used to calculate the gradient of the sampled point position. Matrix multiplication of horizontal edge operator and gray value of the sampled point is used to obtain horizontal edge intensity; similarly, vertical edge intensity is obtained. Where, both the horizontalward edge operator and verticalward edge operator are $3*3$ Sobel operators and:

$$T_x = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ 1 & 0 & 1 \end{bmatrix} \quad T_y = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} \tag{9}$$

Based on the horizontal and vertical edge intensity of the sampling point, the gradient of the sampling point is calculated.

The specific direction of the stroke is calculated by the gradient, and the vertical direction of the gradient is the direction of the stroke, i.e:

$$\alpha = \frac{\pi}{2} - \theta \tag{10}$$

The θ represents the gradient direction of the sampling point.

Taking the core of the sampling point location, the pixels in the $3*3$ neighborhood are selected as the window, and the window edge intensity calculation is performed by the 45° to edge operator with the 135° to edge operator, i.e.:

$$\begin{gathered} c(x,y) = C_1 * I(x,y) + C_2 * I(x,y) \\ C_1 = \begin{bmatrix} 1 & -1 & -1 \\ -1 & 4 & -1 \\ -1 & -1 & 1 \end{bmatrix} \quad C_2 = \begin{bmatrix} -1 & -1 & 1 \\ -1 & 4 & -1 \\ 1 & -1 & -1 \end{bmatrix} \end{gathered} \tag{11}$$

C_1 stands for 45° toward edge operator; C_2 stands for 135° toward edge operator; $I(x,y)$ stands for window pixel point; $c(x,y)$ stands for window edge intensity.

The stroke radius is made explicit by pre-storing a table of edge intensity versus radius relationships. Take the pixel value of the corresponding position of the sampled point on the source image as the brush pixel value. Draw the sample point based on the stroke direction, radius, and pixel value, and set the drawing annotation for all positions to identify the specific drawing state of the corresponding position. Changes the drawing annotation.

II. D.Oil painting generation algorithm flow design

The flow of oil painting generation algorithm based on computer image processing technology is specifically shown in Figure 2.

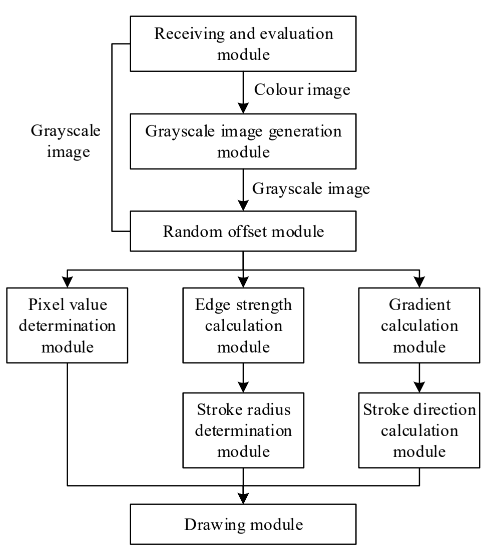


Figure 2: Oil painting generation algorithm process

III. Analysis of the results of the identification of cultural identity in oil painting

III. A. Evaluation indicators and baseline model

In order to evaluate the effectiveness of the proposed method and to verify the differences and advantages between the improved method and other methods in terms of performance, efficiency and robustness, this paper adopts the structural similarity index (SSIM), the peak signal-to-noise ratio (PSNR), and the mean square error (MSE) as the evaluation metrics.

The structural similarity index (SSIM) is commonly used to measure the similarity between two images in image generation tasks and is a widely used image quality metric. Given two images A and B, the structural similarity index is calculated as shown in Equation (12), where μ_A and μ_B are the mean values of images A and B, respectively, δ_A and δ_B are the covariances of A and B, respectively, and C_1 and C_2 are constants used to maintain stability. A larger SSIM value indicates a higher similarity between the two images, and the SSIM value reaches a maximum value of 1 when the two images are identical.

$$SSIM(A,B)=\frac{(2\mu_A\mu_B+C_1)(2\delta_A\delta_B+C_2)}{(\mu_A^2+\mu_B^2+C_1)(\delta_A^2+\delta_B^2+C_2)} \tag{12}$$

Peak Signal to Noise Ratio (PSNR) is an objective criterion for evaluating an image, it is an important measure of signal quality.PSNR represents the ratio between the maximum possible power of a signal and the destructive noise power, the larger the value of the peak signal to noise ratio, the higher the quality of the generated image and the lower the distortion rate. PSNR is commonly used in the field of computer vision to measure the difference between the original image and the processed or compressed image.The formula for calculating the PSNR (dB) between the processed image data X' and the original image data X of size $M \times N$ is shown in Eq. (13):

$$PSNR(X',X)=10\log_{10}\frac{\sum_{i=1}^{M}\sum_{j=1}^{N}MAX_I^2}{\sum_{i=1}^{N}\sum_{j=1}^{N}(X'(i,j)-X(i,j))^2} \tag{13}$$

The mean square error (MSE) is commonly used in regression prediction tasks and is a convenient measure of the average error.MSE is calculated by first finding the difference between each random variable and the mean, then squaring these differences, and finally averaging these squared values.MSE reflects the degree of difference between the estimator and the estimated quantity, and the smaller the value is, the more accurate and better-fitting the machine learning network model is. The smaller its value, the more accurate the machine learning network model is, and the better the model is fitted. Assuming that there are n training data, the true output of each training data is x_i, and the prediction value of the model for each data is $x_{i'}$, the calculation formula of the mean square error of the model under n data is shown in equation (14):

$$MSE=\frac{1}{n}\sum_{i=1}^{n}(x_i-x_i')^2 \tag{14}$$

The baseline models chosen for the experiments are GAN, DualGAN and CycleGAN.

III. B. Data set and experimental environment

The image dataset of the experiment contains some images downloaded from COCO dataset and images obtained and organized using search engines such as Google, Baidu and Sogou, etc. In order to facilitate model training, these data are cleaned and pre-processed, those images with low quality and not meeting the requirements are excluded, and the images meeting the requirements are cropped and resized to 256×256 pixels. The content image dataset contains 5000 images.

The training process uses the Adam optimizer with a learning rate of 0.0001, batch parameter of 16, 300 training rounds, and the values of the loss function weights λ_{cyc}, λ_{id}, and λ_{MS} are set to 0.5, 2, and 4, respectively.

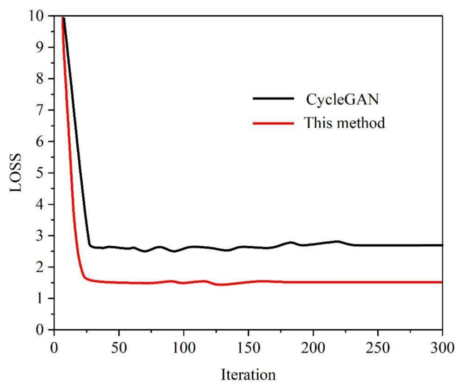
III. C. Performance comparison of oil painting generation algorithms

Under the two image quality evaluation indexes of SSIM and PSNR, the result scores of comparing this paper's method with the three models of GAN, CycleGAN and DualGAN for realizing three different styles of migrations for landscape oil painting images are shown in Table 1. According to the data in the table, in the oil painting style migration, the PSNR value of CycleGAN is slightly higher than the value of this paper's method, but the PSNR value and SSIM value of this paper's method are the highest in both ink painting style and sketch painting style, which indicates that the images generated by this paper's method are more vivid, rich and more similar to the original images. In addition, the SSIM and PSNR values of this paper's method are improved by 0.127 and 1.745 in Landscape→Oil compared to GAN.In summary, the method proposed in this chapter performs the best in the experiments of these three different styles of migration and improves the overall quality of the image and the standard quality metrics as compared to other existing methods.

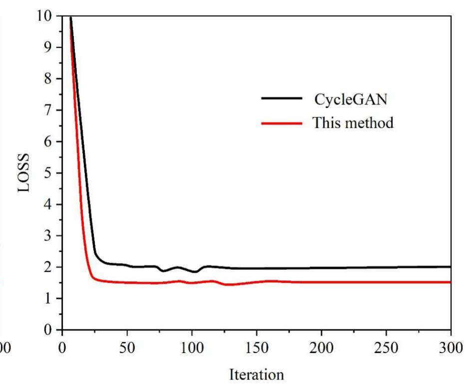
In style migration, the loss function, which is used to measure the difference between the generated image and the target content image and the target style image, plays a very crucial role, and the loss function can reflect the model's performance during the training process, and lower loss values usually mean that the model fits the training data better and generates more realistic and accurate samples. In order to measure the model performance, the average loss functions achieved by the method proposed in this chapter and the CycleGAN method on the three styles in the dataset are compared, and the experimental results are shown in Fig. 3, where (a) ~ (c) correspond to the experimental results of the three styles of oil painting, ink and drawing, respectively. From the figure, it can be seen that compared with CycleGAN, the model of this paper's method can minimize the loss function more effectively, which indicates that the model is the more robust and can generate images that are more in line with the expectations.

Table 1: Quality rating list

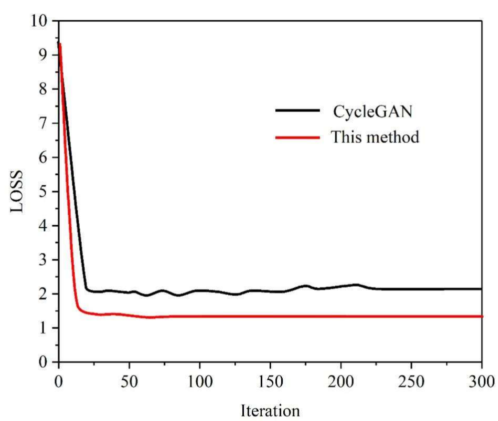
Model	Landscape→Oil		Landscape→Ink		Landscape→sketch	
	SSIM↑	PSNR↑	SSIM↑	PSNR↑	SSIM↑	PSNR↑
GAN	0.611	27.456	0.699	25.451	0.684	23.451
DualGAN	0.675	28.564	0.678	28.120	0.705	26.498
CycleGAN	0.702	29.255	0.712	28.945	0.699	28.647
MSG-CycleGAN	0.738	29.201	0.735	31.456	0.745	30.569



(a)Oil painting



(b)Water ink



(c)sketch

Figure 3: Experimental results of average loss function

III. D. Evaluation results for generating oil paintings

In order to evaluate the generated oil paintings more accurately, we used a combination of automatic model evaluation and manual evaluation. First, we selected 800 works from the generated oil paintings and input them into the evaluation model for scoring. In this process, the model gave the corresponding scores according to the aesthetic quality of the oil paintings. At the same time, we distributed these 800 oil paintings in the form of a questionnaire to both majors and non-majors to assess these works according to their aesthetic views. This was done in order to gather diverse opinions and ratings to get a more comprehensive picture of how the generated oil paintings would perform in an actual aesthetic setting, with scores ranging from 0 to 5.

Table 2 shows the evaluation results of the 800 generated oil paintings. According to the experimental results, the average scores of the automatic and manual evaluations were 4.236 and 4.281, respectively. This indicates that the generated oil paintings have a high quality overall. This result is attributed to our in-depth analysis of the oil paintings and the adoption of corresponding methods, which makes the generated oil paintings show a high degree of realism in terms of color, composition and white space, which is closer to the style of real oil paintings. In addition, these generated oil paintings are well evaluated in terms of aesthetic value, showing that we have successfully preserved the core features of the oil paintings in the process of style migration.

Table 2: The oil painting produces partial evaluation results

Automatic painting number	Automatic evaluation	Automatic painting number	Manual evaluation
1	3.95	1	3.98
2	3.45	2	3.51
3	4.21	3	4.28
4	4.25	4	4.34
5	4.59	5	4.65
6	4.56	6	4.52
7	4.51	7	4.59
8	4.23	8	4.21
9	4.62	9	4.68
10	3.99	10	4.05
Mean	4.236	Mean	4.281

IV. Analysis of artistic expression in oil painting

IV. A. Texture Characterization Statistics and Analysis

There are various texture expression indexes, compared with other texture statistics methods such as grayscale covariance matrix, Tamura method is more meaningful visually for the expression of texture features, which is widely used in the fields of image retrieval, analysis, etc. In this paper, this method is chosen to carry out experiments on the statistics and analysis of texture features.Tamura's research from the psychological point of view has shown that the human vision's perception of texture consists of at least six components, roughness (SCrs), contrast (SCon), direction (SDir), linearity (SLin), regularity (SReg), roughness (SRgh), and so on. Numbers 1-7 represent figure paintings, landscape paintings, still life paintings, animal paintings, historical paintings, custom paintings, and abstract paintings, respectively.

In this paper, the texture index value of each oil painting image is calculated, normalized for analysis, and the mean value is taken for each type of oil painting samples, and each texture index is displayed in groups, and the experimental results are shown in Table 3. The roughness of the texture is a quantity that reflects the grain size of the texture and is one of the most important indicators of texture metrics.The mean value of SCrs is the smallest for No. 5, and the number of texture repetitions is high. Overall, the smaller the roughness SCrs, the smaller the size of the repeated texture primitives and the more times they are repeated, the more delicate the visual effect of the oil paintings.

The contrast of the texture is determined by the range of gray levels, the degree of histogram polarization, the sharpness of the edges, and the period of the repeating pattern, etc. The contrast of No. 7 is the highest, indicating that the foreign oil paintings have a wide range of gray levels.

The directionality of the texture describes the global metric of the texture region. Overall, the directionality SDir from small to large corresponds to the oil painting texture from having no direction to being more directional, with No. 1 having the highest directionality and the strongest stripes.

The linearity of the texture is the average degree of covariance of the edge orientation angles. Overall, the oil painting samples have low linearity. The regularity SReg is related to the standard deviation of roughness, contrast, orientation, and linearity within the local window. Overall, all samples have a high degree of regularity except for oil painting #5, which has an SReg of only 0.45.

The roughness SRgh is a composite of roughness and contrast, with No. 2 having the largest mean SRgh value.

Table 3: Texture index statistics

N	SCrs	SCon	SDir	SLin	SReg	SRgh
1	0.61	0.55	0.64	0.46	0.93	0.55
2	0.60	0.62	0.62	0.25	0.94	0.61
3	0.50	0.49	0.62	0.38	0.92	0.50
4	0.58	0.57	0.54	0.45	0.88	0.57
5	0.46	0.41	0.59	0.33	0.45	0.44
6	0.54	0.50	0.51	0.39	0.91	0.49
7	0.56	0.62	0.55	0.41	0.80	0.60

IV. B. Theme Color Analysis

The theme color for figure painting is usually the skin color of the figure as the main color palette, while other colors are matched to the figure's clothing, background, and other elements. The choice of color for skin tone varies depending on the race, sex, and state of health of the human being. The skin color of the black race is mainly black and black-gray. Yellow skin tones are predominantly fawn. The colors of clothing often vary according to the character status of the person.

The theme colors of landscapes depend on the season of the natural landscape being depicted. Spring landscapes are depicted mostly in green, while summer is dominated by colors such as azure and deep purple. The theme colors of autumn are dominated by golden yellow and red. Winter is dominated by white and blue, reflecting the coldness and tranquility of winter.

The theme color of still life paintings depends on the color of the still life itself, if the still life is mainly flowers, then the theme color is mostly red, purple.

The theme color of animal paintings is based on its own color, with lions in golden yellow and tigers in orange and black.

The theme color of historical paintings is determined by the historical events depicted and the historical background.

The theme colors of custom paintings are mostly based on the folk activities, regional characteristics and the outlook of the times.

There is no fixed pattern for the theme color of abstract paintings, it depends entirely on the subjective intention and emotional expression of the painter, who chooses the theme color according to his own inner feelings and the emotions he wants to express.

V. Conclusion

By establishing an oil painting style migration framework based on improved CycleGAN, this paper has made significant progress in several aspects. The experiments verify the effectiveness of the proposed method, and in the Landscape→Oil style migration task, the SSIM value reaches 0.738 and the PSNR value is 29.201, which is significantly better than the traditional GAN, DualGAN and the original CycleGAN method. The results of texture characterization show that there are obvious differences in the visual characteristics of different types of oil paintings, with figure paintings having the highest directionality index of 0.64, which shows the strongest striation, while abstract paintings have a contrast of 0.62 and the widest range of gray levels.

The proposed improved generator structure effectively incorporates texture prior knowledge by introducing a 4-channel input design, and the application of relativistic discriminator further enhances the local quality of the generated images. The optimized design of the loss function makes the model training more stable and is able to generate high-quality oil painting style images after 300 training cycles.

The comprehensive evaluation of the generated oil paintings shows that the method has good practical value. Among the 800 generated works, the average scores of automatic and manual evaluation reached 4.236 and 4.281, respectively, proving the superiority of generated oil paintings in terms of aesthetic quality and visual effect. The texture statistical analysis further verifies the uniqueness of different thematic oil paintings in terms of color matching and compositional features, providing a scientific basis for the digital creation of oil painting art. This study not only advances the application of computer vision in the field of art, but also opens up a new way for the digital inheritance of traditional art forms.

References

[1] Evans, M. (2016). Painting with Oil. Dissent, 63(2), 11-15.

[2] Zhang, Y. (2017, May). Personal Emotional Expression in the Creation of Oil Painting. In 2017 International Conference on Culture, Education and Financial Development of Modern Society (ICCESE 2017) (pp. 530-532). Atlantis Press.

[3] Shi, Y., & Tsetsegdelger, D. (2024). A Multidimensional Exploration of the Mechanism of Color Emotion Elicitation in Oil Painting under the Perspective of Psycho-Aesthetics. International Journal of Education and Social Development, 1(2), 20-23.

[4] Calderón-Mesén, P., Jaikel-Víquez, D., Barrantes-Madrigal, M. D., Sánchez-Solís, J., Mena-Vega, J. P., Arguedas-Molina, J., ... & Herrera-Sancho, O. A. (2023). Multidisciplinary approach to the study of large-format oil paintings. Scientific Reports, 13(1), 2143.

[5] Cui, F. B. (2023). A Probe into the Modernity of Chinese Oil Painting. International Journal of Advanced Culture Technology, 11(1), 198-203.

[6] Yang, L. (2025). The Fusion of History and Innovation: Re-creation of Traditional Elements in Contemporary Oil Painting Art. Mediterranean Archaeology and Archaeometry.

[7] Wang, R. (2019, January). Research on Chinese Elements in Modern Oil Painting Creation. In 2018 International Workshop on Education Reform and Social Sciences (ERSS 2018) (pp. 409-412). Atlantis Press.

[8] An, Z., & Nie, D. (2023). Impact Of Chinese Cultural Elements On Spiritual Expression In Oil Painting Imagery Landscape: An Exploratory Study In Arts Education. Arts Educa, 37.

[9] Yang, G. (2021). Inheritance and development of national elements in contemporary Chinese, American and Russian oil paintings. Linguistics and Culture Review, 1-15.

[10] Xinyuan, S. (2025). Exploring the Inheritance of Aesthetic Thinking in Chinese Contemporary Oil Painting. International Journal of Advanced Culture Technology, 13(1), 396-402.

[11] Yang, G. (2021). The imagery and abstraction trend of Chinese contemporary oil painting. Linguistics and Culture Review, 454-471.

[12] Zhang-Yu, C., García-Díaz, S., García-Romero, D., & Lalueza, J. L. (2021). Funds of identity and self-exploration through artistic creation: addressing the voices of youth. Mind, Culture, and Activity, 28(2), 138-151.

[13] Munday, J., Sajid, A., & Reader, B. (2014). Cultural identity through art (s) making: Preservice teachers sharing ideas and experiences. Australian Journal of Teacher Education (Online), 39(7), 14-30.

[14] Roald, T., & Lang, J. (Eds.). (2013). Art and identity: Essays on the aesthetic creation of mind (Vol. 32). Rodopi.

[15] Fabryka-Protska, O., Pastushok, T., Kaplun, T., Gunder, L., & Hudakova, J. (2024). Cultural identity and its influence on performing arts: Archetypes, reflections, interpretations. Multidisciplinary Reviews, 8.

[16] Mason, R., & Vella, R. (2013). Lessons about identity formation from contemporary art. International Journal of Education through Art, 9(2), 235-252.

[17] Wang, B. (2023). Oil painting within the framework of art education to support local ethnic cultures and preserve cultural heritage in China. Arte, Individuo y Sociedad, 35(4), 1275.

[18] Zhipeng Yang,Yuhao Pan,Wenchao Liu,Jinhao Meng & Zhengxiang Song. (2025). Enhanced fault detection in lithium-ion battery energy storage systems via transfer learning-based conditional GAN under limited data. Journal of Power Sources,645,237192-237192.

[19] Chao Xu,Jiajun Li,Xiangyu Yun,Fengxi Yang & Xin Liu. (2025). Studies of electrical capacitance tomography image reconstruction based on improved CycleGAN. Flow Measurement and Instrumentation,105,102927-102927.

[20] Tolpadi Aniket A,Luitjens Johanna,Gassert Felix G,Li Xiaojuan,Link Thomas M,Majumdar Sharmila & Pedoia Valentina. (2023). Synthetic Inflammation Imaging with PatchGAN Deep Learning Networks.. Bioengineering (Basel, Switzerland),10(5).