A Study of Expression and Creation of Picture Space in Painting and Photography Based on a Microscopic Perspective

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Abstract: Photography technology and painting influence each other at the beginning of the invention of photography, the micro perspective of photography technology has changed the way people observe things, so that many painters began to use photography as a creative material to complete the paintings. The article firstly combed the expression form and aesthetic characteristics of painting art, and analyzed the application performance of painting art form in photography. A reversible Flow model is used to build an encoder-decoder to obtain the features of the photographic image, and then a realism smoothing module is introduced to complete the style alignment between the stylized features and the content features of the photographic image, and to optimize the realism style migration effect of the photographic image by combining the style loss and the optimal transmission loss. The photographic realism style is stronger than the subjective evaluation experiments of painting creation to analyze the integration effect of painting creation and photographic images. The FID value of the photorealistic style migration model is 184.16, which is 17.76% lower than the BiGAN model. The overall evaluation score of the painting was 4.075 when the painting was created using the style images generated by photorealism. The micro perspective explores the extent to which the composition, color and graphics of photographic images influence the creation of paintings, which helps paintings to access the spatially created forms of photographic images.
Keywords: Reversible Flow Model; Realism Smoothing; Optimal Transmission Loss; Style Migration; Painting and Photography

1. INTRODUCTION

Photography is a young art for painting, with a history of only more than one hundred years, and in today's period of rapid media development, photography as the most concise way to capture things, how to shoot good works is a problem worthy of in-depth exploration (Anderson-Tempini, 2017; Barnbaum, 2017; Grundberg, 2021; Hill, 2020). The expression of formal beauty in paintings in modern photography can promote the combination of form and content of photographic works, and utilize the viewpoint of painting aesthetics to guide the development of photography, so as to create more excellent photographic works (Kantrowitz, 2022; Soutter, 2018; Theoodore, 2023). In the field of contemporary visual art, the fusion of painting and photography opens up a new way of expression, mixing the traditional and technical advantages of the two media. This fusion not only challenges the boundaries of art, but also provides artists with unlimited creative space (Banou, 2020; Peddecord, 2022; Simmons, 2019; Yuktirat, Sindhuphak, & Kiddee, 2018). Painting, as an ancient art form, relies on the artist's manual skill and subjective expression to convey emotion and visual depth. Photography, on the other hand, as a medium younger than painting, relies on mechanical devices to capture the objective truth of real moments (Fang et al., 2023; Lee, 2017; Riley, 2021; Zhang, 2024). When these two forms are combined, the authenticity of photography and the expressive power of painting interact to produce a new visual language, one that can cross the boundaries between the real and the imagined, allowing the viewer to experience the depth and complexity of art in more dimensions (Browning, 2020; Lima et al., 2021; Wells, 2021). In this way, artists can not only explore new techniques and materials, but also introduce more layers and depths into the visual narrative, thus enriching the viewer's perception and understanding (Al-Kire et al., 2023; Whistler, 2019). Today's painting has been influenced by the art of photography in its creation, and the composition, expression techniques, light and color under the microscopic perspective of photography have been widely used in the creation of painting to promote the expression and presentation of the language of painting in the contemporary cultural context. This paper analyzes the aesthetic characteristics of painting art from the expression of painting art, and discusses the layout performance and spatial mood creation of painting art form in photography. The encoder and decoder of photographic images are established by reversible Flow model to obtain the basic features of photographic images, and combined with the realism smoothing module to realize the stylization of photographic images and the alignment of content features. For the performance and spatial creation of painting and photography from the micro perspective, this paper designs subjective evaluation experiments from three perspectives, namely, composition, color and graphics, which provides a new research path for the study of photographic images to assist the creation of paintings.

2. REPRESENTATION OF TRADITIONAL FORMS OF PAINTING AND PHOTOGRAPHY

Photography and painting, as two different disciplines, are both independent and integrated with each other. Photography is the instantaneous memory left directly after a person finds beauty. Painting is a product that is recreated through the brain and hands of a person who has discovered beauty. People can paint digitally through computer software using cell phones, tablet PCs, etc., which provides more possibilities for painting while realizing digital image preservation. In addition, computers likewise provide photographers with more ways to process their photographic works and new forms of creation.

2.1 Expressions and Aesthetics of Painting Art

2.1.1 Expressions of the Art of Painting

Any artistic creation of painting is based on sketching, coloring and sketching. Regardless of the genre, it is necessary to express the objective world with “meaning”, and integrate the writer's subjective will and personal feelings into the creation, only in this way can we create works of art that reflect a certain aesthetic consciousness. The expression of painting art mainly includes the dimensions of modeling language, mood expression, and aesthetic concept to promote the innovative development of paintings (Winfield, 2023).

(1) In terms of modeling language, the art of painting expresses form, chiaroscuro, emotion and other elements with lines, brush and ink, color and other elements, which constitute a unique modeling language system and spiritual mood. Photography draws on the ink and brush language of painting to make the emotions in photography works richer and deeper, and to achieve emotional resonance with the viewers.

(2) In terms of mood expression, painting emphasizes the spiritual connotation of things, expressing certain emotions or ideas through the expression of natural scenery and figures. The atmosphere and mood created by its unique techniques and expressions can guide the viewer to some kind of emotion or aesthetic concept.

(3) In terms of aesthetic concepts, the art of painting emphasizes nature, harmony, introspection, subtlety, elegance, etc., which can lead to a more

profound aesthetic perception, a better grasp and application of aesthetic concepts, and the creation of works with more connotations and ideology. You can better grasp and use the composition, color and other techniques, so that the works achieve a more harmonious, natural, elegant aesthetic effect.

2.1.2 Aesthetic Characteristics of Painting Art

The aesthetic characteristics of painting art cover two aspects: inner spirit and outer form, whose specific performance is shown in Figure 1. The inner spirit is the root of the outer form, while the outer form is the carrier and expression of the inner spirit, which are interdependent and inseparable, and together constitute the unique artistic language and aesthetic style of painting, showing profound ideological connotations, profound emotional experience and unique artistic charm.

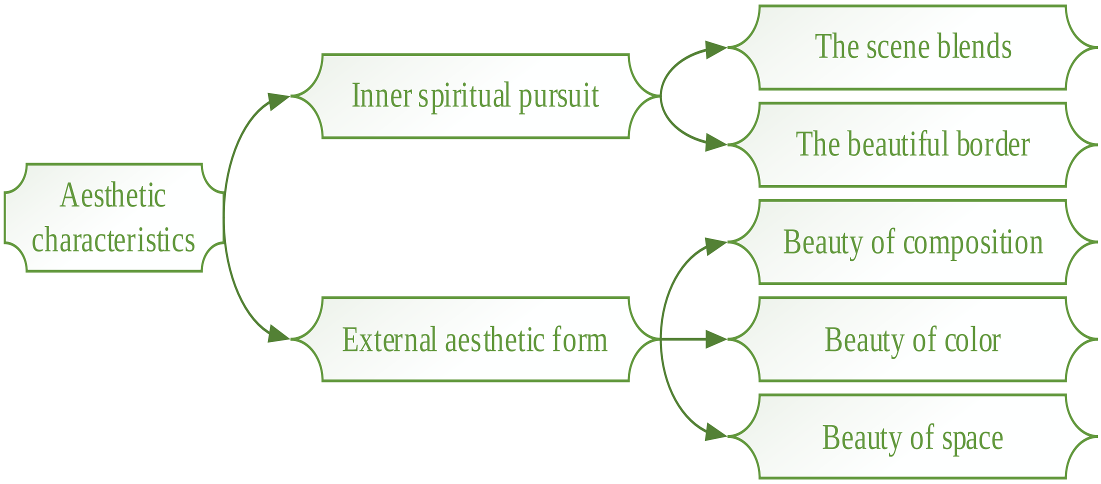


Figure 1: Aesthetic Characteristics of Painting Art

The inner spirit in the art of painting refers to the artist's in-depth thinking and realization of the natural world, human society, morality and ethics. This inner spirit contains the philosophical thoughts, values and aesthetics of traditional culture, emphasizes the harmonious relationship between man and nature, man and society, and highlights the subject's initiative and the philosophy of taking the realm as high.

The external aesthetic form is the artistic expression of painting, this visual language of visualization is influenced by philosophy and aesthetics, from the ink and brush, line, layout, color, space and other aspects of the comprehensive display of painting form and spirit, vivid artistic charm. The artist conveys emotions through the appropriate white space, showing the realm of scenario integration, creating a profound and introspective beauty for the viewer.

2.2 Representation of Painting Forms in Photography

2.2.1 Representation of Painting Layout from a Microscopic Perspective

Under the influence of the art of painting, artists focus on the use of painting forms in photographic creation, artists in the creation of the composition of the picture through a microscopic point of view, color, perspective form of expression, and photographic works have gradually shown the form of painting form of the form of both God and spirit, the rhythm of the vivid, the scene of the integration of the aesthetic characteristics. The continuation of the aesthetic habit of painting and the promotion of consciousness influence the development of photography, and the fusion of painting form and photography makes the photography works present the visual effect of the beauty of mood and form. The appropriation of painting and photography is shown in Figure 2, which mainly includes three techniques of composition, color and perspective, so as to emphasize the form and spirit of painting, vividness, and to realize the mood of the mood and scenery.

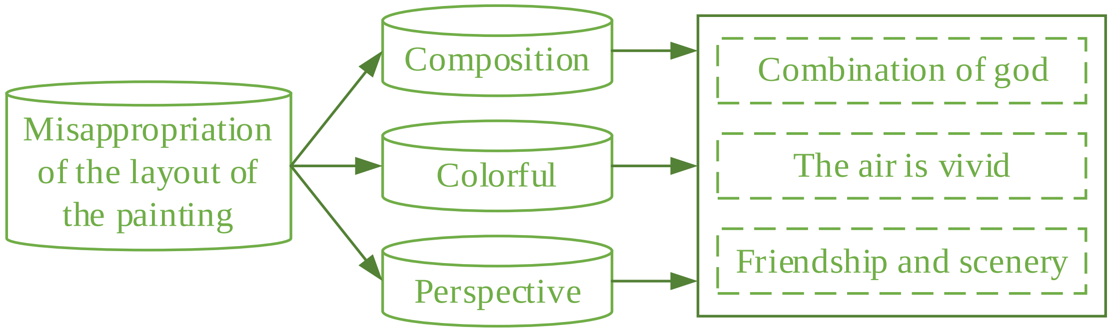


Figure 2: Misappropriation of the Layout of the Painting

(1) Composition refers to the painter's arrangement of the contents of the picture, so that the arrangement of the elements in the picture tends to harmonize. Painters do not present their works in a fixed form or at a fixed time, but instead apply a more flexible approach, arranging the objects in the world according to their own artistic habits and ideas to create the painter's inner world.

(2) In the process of creating traditional paintings, painters often use the amount of water in the ink and water, as well as the speed of the brush strokes and the different strokes and strokes, to create a variety of shades in the picture.

(3) In painting, painters use multi-point or three-point perspective, which means moving up and down, left and right, and forward and backward, observing the scenery to take in the scene and choosing the composition of the picture, so as to make the picture reflect the unique freedom and flexibility of Chinese painting. In addition, the composition

of traditional paintings also emphasizes the contrast between reality and falsehood in the picture, emphasizing that there is reality in the falsehood of the picture, and that there is falsehood in the reality at the same time.

2.2.2 Spatial Context Creation in Micro Perspective

The expression of artistic meaning in a work is to make the principle of the Divine shine through the net of order. This mesh of order is organized by each artist's artisanal craftsmanship into an organic and harmonious art form of lines, dots, light, color, form, sound, or words, in order to express the meaning. This suggests that works of art need to express mood with the help of specific elements in a microscopic perspective, paintings through light, color, and so on. From this further analysis, photographic works to have a mood, inevitably affected by the composition, light, color, shadow and other stylistic elements. Only a clear understanding of the composition of the photographic mood, in order to better understand the beauty of its photographic mood, and then to ensure the creation of the spatial mood of the photographic image.

The creation of the spatial mood of the photographic image is shown in Figure 3, through the harmony and unity of color to achieve emotional expression, while making the image modeling more full and thick, more rendering and highlighting the mood of the work. The use of light to give the photography work more natural and smooth characteristics, in the photography process not only plays a role in modeling, but also lead the viewer into a mood, control the light to make the work produce excellent aesthetic effect. Combined with the diversity of the form of lines to enhance the artistic impact of the work, so that the shape of the work of God to achieve unity, giving people a sense of beauty to enjoy.

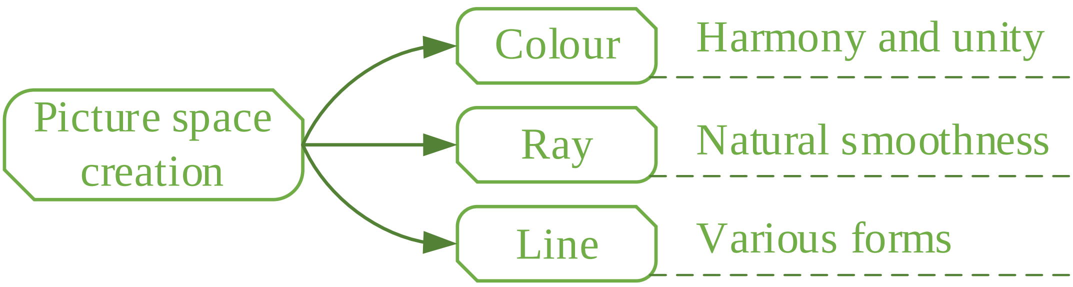


Figure 3: The Construction of the Space of Photographic Space

3. DEEP LEARNING-BASED REALISM STYLE MIGRATION

The continuous development of the times has led to the rapid progress of photography technology, and the images thus obtained have gradually replaced the documentary and inheritance functions of paintings, bringing a considerable impact on traditional easel paintings. Photography and painting are both forms of visual art, and the development of photographic technology provides reference for painting, promotes the diversified expression of painting language, and inspires painters' inspirations for painting themes, styles, forms, languages and other aspects. At the same time, the development of painting also provides new creative ideas for photography in terms of composition, color, and image organization. Both photography and painting are changing their traditional patterns and forming new styles through mutual reference and influence.

3.1 Photographic Realism Style Migration Model

3.1.1 Model basic Network Structure

In order to visualize the realism of photographic works on top of paintings, this paper proposes a photographic realism style migration model based on the generalized realism smoothing plug-in (SMP), and the model results are shown in Fig. 4. The model results are shown in Figure 4. It is mainly divided into encoder, realism smoother and decoder. Firstly the pre-trained reversible model Flow is used as an encoder to extract the content and style image features, secondly the realism smoother consists of five smoothing layers, the smoothing layer is used to complete the style alignment between the artistic stylized features and the content features, and finally the features are mapped back to the image using a decoder with a style preserving connection to generate the final realism stylized image (Jalilova, 2022).

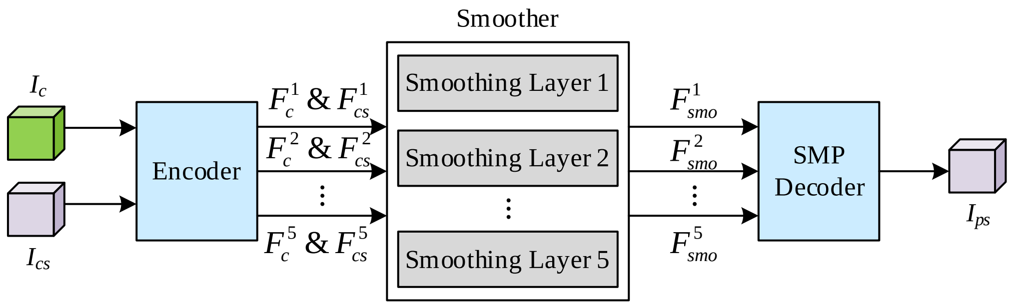


Figure 4: Photographic Reality Style Migration Model

3.1.2 Realism Smoothing Module

In order to reduce the local distortion of the stylization results and to provide finer-grained control over the smoothing process, the realism smoother in this chapter consists of five smoothing layers and uses a local style alignment algorithm in the smoothing layers to accomplish the style alignment between the artistic stylization features and the content features.

The smoothing layers enhance the visual quality of the stylization result and make it look more realistic.

Given the encoded content feature Fc and the artistic stylization feature Fcs, the realism-smoothing feature is generated:

$$F_{smo}(j) = \frac{Fc(i) - \mu_c(i)}{\sigma_c(i)} \cdot \sigma_{cs}(i) + \mu_{cs}(i), \forall j \in N(i) \tag{1}$$

where "·" denotes the elemental product, i, j denotes the spatial location of the feature map, $\mu(i)$, $\sigma(i)$ denotes the local mean and local standard deviation maps at location i, and the local mean and standard deviation feature maps can be efficiently computed by convolution as:

$$\mu_v = F_v * h_a = \sqrt{F_v^2 * h_a - \mu_v^2}, \forall v \in \{c, cs\} \tag{2}$$

where h_a denotes the kernel of the mean value filter of size $p \times p$. Layer k realism smoothing feature is given by:

$$P_{smo}^k = \frac{P_c^k - \mu_c^k}{\sigma_c^k} \cdot \sigma_{cs}^k + \mu_{cs}^k \tag{3}$$

where F_{smo}^k denotes the realism smoothing feature of layer k.

3.2 Feature decoding and loss function design

3.2.1 Image feature coding and decoding

In the style migration task, most of the existing studies use linear networks as generators and employ adversarial learning strategies to train the networks. However, the pooling operation involved brings about spatial feature loss, and the accumulated feature mapping loss may disturb image detail generation and cause information loss. The stream model, on the other hand, is theoretically free of reconstruction errors and is a generative model capable of establishing an accurate mapping between the image domain and the potential space. Therefore, this paper focuses on extending this reversible model architecture for photographic realism style migration scenarios. In this paper, we use the existing reversible model Flow as the basic processing module for image coding-decoding (Bao, Li, & Lu, 2024). Its basic working principle can be expressed as follows:

$$z_c = f(I_c)$$

$$z_s = f(I_s)$$

$$I_{cs} = f^{-1}(AdaIN(z_c, z_s)) \tag{4}$$

Where mappings $f: \mathbb{R}^D \to \mathbb{R}^D, f^{-1}: \mathbb{R}^D \to \mathbb{R}^D$ represent the forward and inverse transformation process of the Flow module, the inputs of mapping f are the content map and the stylized map, and the outputs are the respective encodings. The input of the inverse mapping f^{-1} is the encoding of the content style map, and the output obtains the stylized image. And, the optimization objective function of f is:

$$= \mathbb{E}_x \left[- \log p_z \left(f_\theta(x) \right) - logdet \left| \frac{\partial f_\theta(x)}{\partial x} \right| \right] \quad (5)$$

Where x denotes the real data, θ denotes the parameters that can be learned, $p_\varepsilon(x)$ denotes the complex distribution of the image domain, $det|\cdot|$ denotes the Jacobi determinant, and $p_z(\cdot)$ denotes the Gaussian distribution of the potential space.

In order to enhance the model's ability to represent spatial details, this paper introduces the Haar wavelet into the traditional affine coupling layer, and utilizes the discrete wavelet to obtain the high-frequency information that is not easy to extract from the image, and strengthens the learning of spatial edges, and textures. In this paper, a multi-scale discrete wavelet pyramid structure is used to enhance the adaptation of the coupling layer to the style migration task. The system of equations for the specific operation of a single WAC layer, including forward and backward passes, is denoted as:

$$\begin{cases} Forward - feed: \begin{cases} x_1, x_2 = split(x) \\ y_1 = x_1 \\ y_{haar}\left(K_{haar}\left(h_{conv}(x_1)\right)\right) + x_2 \\ y = concat(x_1, x_2) \end{cases} \\ Inverse - feed: \begin{cases} y_2 = y_2 = split(y) \\ x_1 = y_1 \\ y_2 = K_{haar}^{-1}\left(K_{hoar}\left(h_{conv}(y_1)\right)\right) - y_2 \\ x = concat(y_1, y_2) \end{cases} \end{cases} \quad (6)$$

In this case, the transform processing based on Harr wavelet including forward analysis K_{haar} and inverse reconstruction K_{hada}^{-1} is given by Eq:

$$Haar - Wavlet: \begin{cases} I_l: \{I_l, D_l\} = K_{haar,l}(I_{l-1}) \\ \hat{I}_{l-1}: \{\hat{I}_{l-1}, \widehat{D}_{l-1}\} = K_{haar,l-1}^{-1}\left(I_l, h_{conv,l}(D_l)\right) \end{cases}, l \in 1,2, \dots L \quad (7)$$

where the $split(\ \ )$ function splits the tensor into two halves along the channel dimension, the $concat(\ \ )$ function joins the two tensors along the channel dimension, and $h_{conv}(\ \ )$ is a simple convolution operation.

3.2.2 Model Loss Function Design

In this paper, the definition of the loss function is changed based on the design of the existing image style migration loss, and a linear combination of the optimal transmission distance loss and pixel loss is introduced as the content loss of the content image. The total loss function for style migration is determined by a weighted summation function consisting of the optimal transmission loss and the style loss. This combined loss function can effectively balance the style and content information between the generated image and the target image, and produce high-quality and natural image reconstruction results.

(1) Style Loss: The style loss of the photorealistic style migration model designed in this paper uses the feature-computed Gram matrix output from the Relu_2, Relu_2, Relu_3, Relu_3 layers of VGG19 (Yang et al., 2024). The Gram matrix can be expressed as:

$$G_j^{\Psi}(x)_{c,c'} = \left(1/\left(C_j H_j W_j\right)\right) * \sum_{h_n=1}^{H_j} \sum_{n=1}^{\pi_j} \psi_j(x)_{h_n c} \psi_j(x)_{h_n c'} \quad (8)$$

The style loss calculation is expressed as:

$$L_{style}^{\psi,j}\left(\hat{f}, f\right) = \left\|G_j^{\psi}\left(\hat{f}\right) - G_j^{\psi}(f)\right\|_F^2 \quad (9)$$

Where, G is the Gram matrix, $G_j^{\psi}(x)_{c,c'}$ is the inner product of $\psi_j(x)_{h_n c}$ and its transpose $\psi_j(x)_{h_n c'}$ in layer j of the VGG network, $L_{style}^{vj}\left(\hat{f}, f\right)$ is the style loss, $G_j^{\psi}\left(\hat{f}\right)$ is the Gram matrix of the generated image, and $G_j^{\psi}(f)$ is the Gram matrix of the stylized image.

(2) Optimal transmission loss: Unlike the generative reconstruction of an image in the pixel domain, the reconstruction of a drawn image is a mapping relationship from the pixel domain to the spatial domain, and in this chapter, the optimal transmission distance is used as an effective measure of the similarity loss between the canvas and the reference image. The optimal transmission model with smooth join entropy regularization is expressed as:

$$J_{\epsilon}\left(h, \hat{h}\right) = min_{P_{\sigma}(h,\hat{h})} \langle D, P \rangle - (1/\lambda) R(P) \quad (10)$$

where $\langle\cdot\rangle$ is the inner product, $J_c\left(h, \hat{h}\right)$ is the total transmission distance between the two distributions, $w\left(h, \hat{h}\right)$ is the set of constraints, $P \in \mathbb{R}_+^{n \to n}$ is the joint probability matrix, the discrete entropy $R(P)$ is the regular term, and $R(P)$ is denoted as:

$$R(P) := -\sum_{i,j=1}^{n} P_{i,j} \log P_{i,j} \quad (11)$$

Then the optimal transmission loss function is expressed as:

$$L_{ot}\left(h, \hat{h}\right) = \langle D, J_{\epsilon} \rangle \quad (12)$$

Where h is the rendered painting, $\hat{h}$ is the reference photographic image, and matrix D represents all the transportation costs of moving a "unit of pixel mass" from one position in h to another position in $\hat{h}$.

(3) Total Loss Function: The total loss function is a weighted summation function consisting of the optimal transport loss and the style loss. I.e:

$$L_{total} = \beta_{ot} L_{ot} + \beta_{style} L_{style} \tag{13}$$

where $\beta_{ot}, \beta_{style}$ are the weighting coefficients of the optimal transmission loss and the stylization loss, respectively, which together control the balance of the objective function.

3.3 Photographic Realism Style Migration Experiment

3.3.1 Model Loss Function Changes

During the model training process, the dataset used is Microsoft COCO, which contains more than 50,000 photographic images, and the model parameters are iterated using the Adam optimizer, which can adaptively adjust the learning rate according to the momentum theorem to accelerate the training speed of the model, and the learning rate is initially set to 0.0001, the batch size is set to 5, and the epoch is set to 10. The loss function proposed in Section 3.2.2 can gradually transfer the knowledge of photographic image style migration to the model during the iterative optimization process. The loss function proposed in section 3.2.2 of this paper can gradually transfer the photographic image style migration knowledge to the model during the iterative optimization process. Figure 5 shows the convergence process of the loss function during model training. As can be seen from the figure, both the style loss term and the optimal transmission loss term during the training process will gradually decrease in the backpropagation process until convergence, and the loss values of both are stabilized at 82.37 and 72.35 after 200 rounds of iterations. The model-generated photographic stylized images did not have a large gap with the painting images in terms of overall visual performance. Overall, the model-generated photographic stylized images have only partial loss in pixel accuracy, and the model-generated photographic stylized images have stylized texture features that can be effectively obtained from photographic images, with the final loss value stabilized at about 81.64. This indicates that the style migration knowledge available in the model has been more completely realized transmission, and in the training process, the model learns new photographic style migration knowledge by virtue of the loss function. By applying it to painting creation, the composition, color, texture and other changes of the photographic image can be obtained, so as to create a more meaningful painting space.

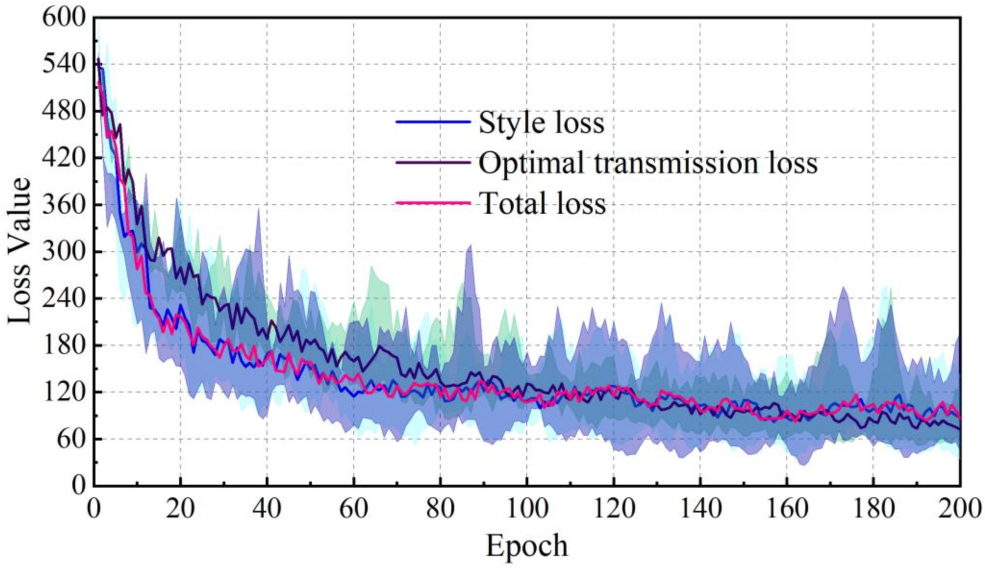


Figure 5: The Convergence of the Loss Function

3.3.2 Photorealistic Style Migration

In order to further verify the knowing effect of the photorealistic style migration model designed in this paper for painting creation, it is investigated whether the painting style images are integrated into the style of photorealistic images. Three kinds of measurement indexes, namely, FID parameters, PSNR, and IS score, are used to compare the image stylization effect obtained by this paper's method with other methods, and AdaIN, CycleGAN, SANet, BiGAN, and Pix2Pix are mainly chosen as the comparison methods. The scores of quantitative indexes after the experiment are shown in Figure 6. The PSNR index and IS index scores of this paper's model in the experiment are 80.63 and 88.79, respectively, which are higher than those of both the comparison models, and the FID is used to measure the difference between the real image and the generated image in the distribution of feature levels. The FID index score of the method in this chapter achieved the lowest value of 184.16, which indicates that the new style images generated by the model proposed in this paper are closer to the artistic style of photographic images, and the distribution of the style information of the generated images is close to the data distribution of the style information of photographic images. The Pix2Pix model with sub-optimal performance is able to focus on the part of commonality between the two domains by introducing contrast learning, but ignores the part of difference between the two domains, which makes the image outline unclear. The introduction of reversible Flow model in this paper's method enhances the connection between distant pixels in a photographic image, which can make the style-migrated image obtain clearer edges. Therefore, the image generated by this paper's method is of higher quality, with less distortion between it and the original photographic image, and its application in painting creation can help creators to get the inspiration of photographic image expression and improve the spatial expression ability of painting creation.

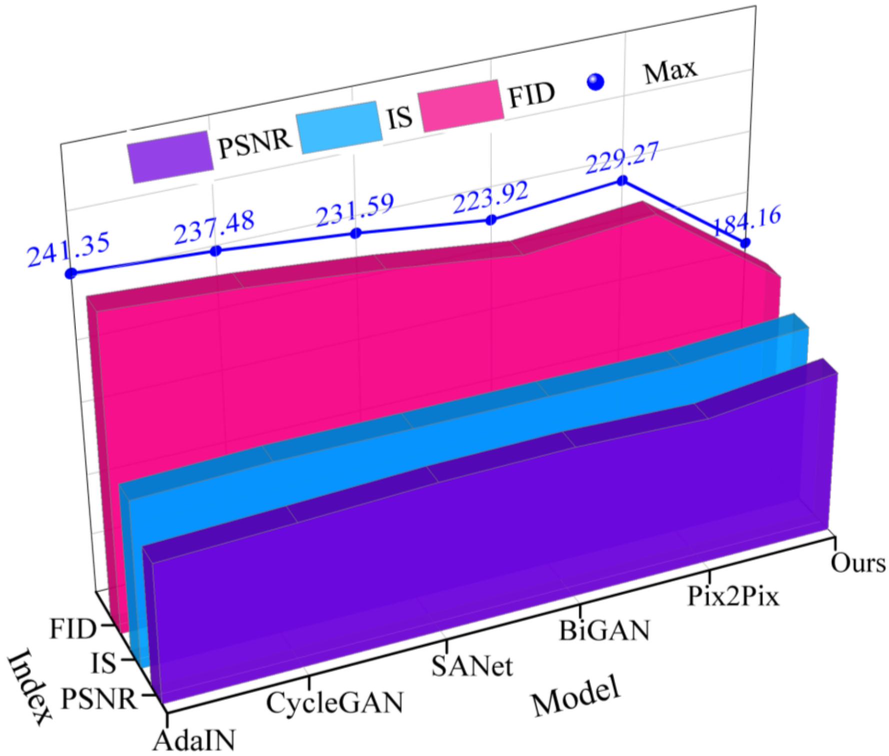


Figure 6: The Effect of the Photography Realism Style Migration Effect

3.3.3 Analysis of Model Operational Efficiency

In this paper, from the integration development degree of painting and photography, if the efficiency of the algorithm is low, it is difficult to fully display the photographic image in the painting creation, which makes it difficult to enhance the expression ability of the painting creation design in terms of mood, and it is difficult to be used as an effective design method for the painting creation pattern, so it is necessary to evaluate the efficiency of the style migration model. In this paper, the control variable method is used as the experimental method to evaluate the conversion efficiency of the model from the perspectives of whether the model needs to be trained (A), whether it supports the conversion of any style (B), the demand of photographic images (C), the effect of style of photographic images (D), and the speed of conversion (E), etc., and its operational efficiency is shown in Table 1. From the data in the table, it is concluded that the style migration processing of photographic images using the AdaIN model requires a large number of style images as training conditions. And for all sizes of photographic patterns stylization time is relatively long, from the subjective conditions to evaluate the quality of the image, this method plays a certain effect on color-rich patterns, but less effective for patterns with a single color. The model based on BiGAN and Pix2Pix model can process patterns with arbitrary color richness, and the style conversion time is shorter, and the time for converting a 512*512 size photographic image in this experimental environment is 7.042s and 9.515s respectively. The model designed in this paper generates higher quality images although the training and style conversion process takes slightly more time. Among them, the style migration encoding and decoding method based on reversible Flow model is shorter compared to the instance normalized fast style migration method in terms of conversion time, and the PSNR and IS values are higher, which is more effective. In summary, the photographic image style migration model in this paper has two main advantages, one is that it can play a good painting creative expression effect, which is very suitable for the creative design of the pattern of painting creation, and the other is that it can undertake a large number of photographic pattern stylization tasks, so as to expand the pattern database of the painting creation, and provide a certain reference value for improving the stylized expression of painting creation.

Table 1: Operational Efficiency Analysis of the Model

Variable	AdaIN	CycleGAN	SANet	BiGAN	Pix2Pix	Ours
A	Yes	No	115 min	128 min	134 min	121 min
B	Yes	Yes	Yes	Yes	Yes	Yes
C	Many	One	One	One	One	One
D	Poor	Good	Good	Good	Good	Excellent
	128*128	3.412 s	> 1.5h	0.748 s	1.097 s	0.842 s
E	256*256	15.718 s	> 1.5h	2.665 s	4.218 s	4.205 s
	512*512	>0.5 min	> 1.5h	7.042 s	9.515 s	9.448 s

4. SUBJECTIVE EVALUATION OF PAINTING CREATION SUPPORTED BY PHOTOGRAPHIC IMAGES

In the field of contemporary visual art, the fusion of painting and photography has opened up a new way of expression, mixing the traditional and technical advantages of the two media. This fusion not only challenges the boundaries of art, but also provides artists with unlimited creative space. In this way, artists are not only able to explore new techniques and materials, but also introduce more layers and depths into the visual narrative, thus enriching the viewer's perception and understanding.

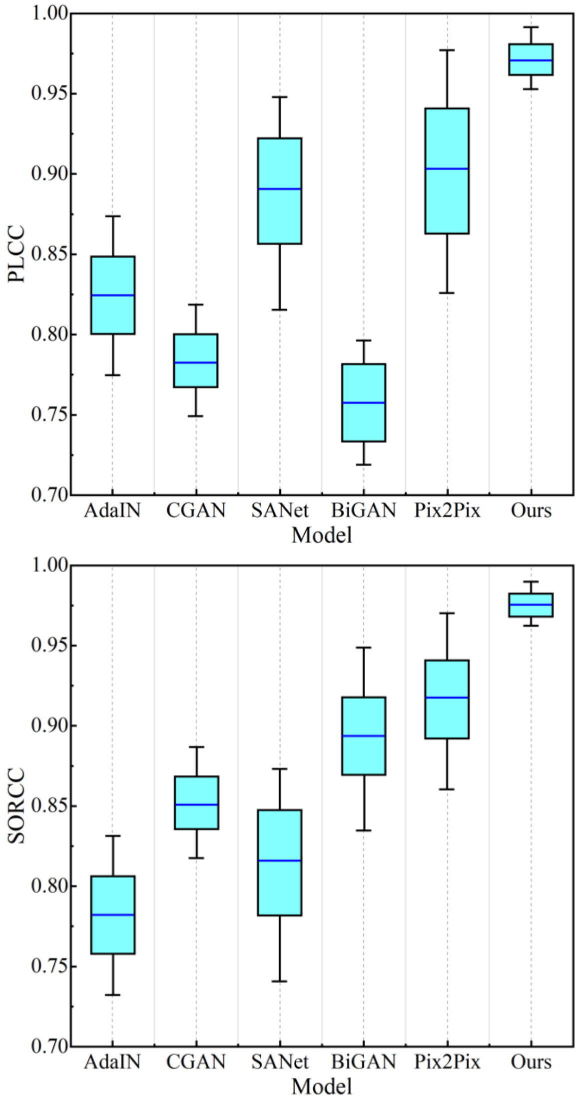
4.1 Analysis of Subjective Evaluation of Photographic Works

4.1.1 Selection of subjective evaluation indicators

The result of subjective evaluation is an important factor to measure whether the objective metrics are advanced or not. The subjective evaluation method in this study mainly refers to the subjective quality scoring method (MOS), the subjective scorer consists of 15 computer vision researchers, the subjective scorer needs to evaluate the generation quality of the photographic images from the same experimental environment, by observing the color, clarity, and the presence of misalignment or ghosting for the photographic images to be scored, the scoring interval is [0,100], the value of the subjective score The larger the value of the subjective score, the better the quality of the generated photographic image, and vice versa. In order to measure the superiority of the performance of objective indexes, the correlation between objective scores and subjective scores was measured by using Pearson's rank correlation coefficient (PLCC) and Spearman's rank correlation coefficient (SROCC).The values of PLCC and SROCC are both in the range of [-1,1], and the closer the value is to 1, which indicates that the higher the degree of consistency between the objective indexes and the results of the subjective evaluation, the higher the quality of the photographic image generation and the better the quality for the creation of paintings and drawings. The higher the quality, the higher the ability to express the mood and picture provided for the creation of paintings.

4.1.2 Analysis of subjective evaluation results

In order to test the consistency of the photorealistic image style migration model designed in this paper with the subjective evaluation scores (MOS), this paper chooses PLCC and SROCC as the evaluation criteria, and selects different models for comparison, and obtains the comparison results of different models as shown in Fig. 7. Among them, Fig. 7(a) and Fig. 7(b) show the PLCC and SORCC box line plots of the models after 1000 iterations, respectively. As can be seen from the figures, the median PLCC and SORCC of the photorealistic image style migration evaluation scores and subjective evaluation scores designed in this paper can be up to about 0.975, which indicates that the evaluation results of photographic image generation obtained by the model in this paper are very similar to the subjective scores. Comparatively speaking, the PLCC and SORCC of AdaIN, CGAN and SANet models are basically lower than 0.9, and the photographic image generation results of this paper's model are better. This paper's model reduces the correlation between image color features when style migration is performed for photographic images, which makes the gap between the pixels of photographic images increase, but improves the extraction effect of photographic image features through the invertible Flow model, and effectively improves the evaluation score of photographic image generation.



(a) PLCC (b) SORCC

Figure 7: Comparison Results of Different Models

4.2 Creative effects of painting in photography

4.2.1 Evaluation of the effectiveness of painting creation

Based on the style images generated by the photographic image style migration model, 20 art students were selected from the College of Fine Arts at University Z to create paintings, and subjective evaluations were conducted on the created paintings. The evaluation indexes were set according to the characteristics of the paintings, and the main contents are shown in Table 2, which mainly include the dimensions of composition, color, and graphic expression.

Table 2: Evaluation of The Creation Effect of Painting

Module	Index	Symbol
	Hierarchy richness	T1
Composition	Element richness	T2
	Element richness	T3
	Color richness	T4
Color	Color saturation	T5
	Color brightness	T6
	Profile style	T7
Graphics	Spatial expression	T8
	Artistic expression	T9

Since different elements have different degrees of influence on the effect of painting creation, a weighted scoring method is adopted to arrive at the final evaluation score. The weighting coefficients of the indicators are first determined by expert evaluation, and then the evaluation scores of each indicator are multiplied by the weighting coefficients of the indicators to arrive at the final score. In order to ensure the scientific and reasonable value of the weight coefficients, 10 experts in the field of photographic expression and painting creation were invited to evaluate and score the importance of each indicator, and then determine the weight of each indicator.

4.2.2 Evaluation results of Painting Creation

In order to ensure the validity of the experimental data, 50 graduate students of the Academy of Fine Arts were selected to carry out the evaluation and analysis after the painting creation, and the evaluation questionnaire used a Likert 5-level scale, with 1~5 representing very dissimilar, dissimilar, generally similar, similar and very similar, respectively. The respondents scored the performance effect of each index by comparing the painting creation images with the original photographic images, and the evaluation results of each index were obtained as shown in Table 3. From the evaluation of each index, the evaluation scores of richness of layers, richness of elements, richness of colors, color saturation, brightness of colors and spatial expression of paintings based on photographic image style migration are all higher than 4.15 points. It indicates that the style images obtained from the photographic image style migration model can provide reliable picture guidance for painting creation, and the spatial expression of the style images can help painting creators better create a spatial mood atmosphere similar to that of the photographic images. The scores of element randomness, outline style and mood expression effect are between [3.74,3.85], indicating that the style images obtained by the photographic image style migration model have room for further improvement in element performance, outline style and mood expression ability. The average score of each index is solved by the mean value, and the scores of composition, color and graphic module are 4.059, 4.259 and 3.907 respectively, of which the scores of composition and color module are at the "similar" level, and the graphic is close to the "similar" level, indicating that the scores of each module are at the "similar" level, which means that the scores of each module are at the "similar" level. The scores of the composition and color modules are at the "similar" level, and the graphics are also close to the "similar" level, indicating that the expression of painting creation in each module is good. After solving the mean value of the evaluation scores of each module, the overall evaluation score is 4.075, which is also at the "similar" level. In conclusion, the style images generated based on the photographic image style migration model can help creators to create paintings, better explore the composition and mood expression of photographic images, show the essential characteristics of photographic images through color expression, and enhance the spatial structure of painting creation.

Table 3: Evaluation results of Each Index

Index	**Rating scores (%)**					**Means**	**STD.**
	X1	**X2**	**X3**	**X4**	**X5**		
T1	0.007	0.024	0.168	0.546	0.255	4.151	0.705
T2	0.001	0.000	0.148	0.725	0.126	4.238	0.642
T3	0.003	0.051	0.202	0.578	0.166	3.789	0.591
T4	0.004	0.009	0.054	0.632	0.301	4.334	0.617
T5	0.002	0.038	0.243	0.514	0.203	4.187	0.753
T6	0.000	0.043	0.183	0.629	0.145	4.256	0.658
T7	0.005	0.102	0.159	0.548	0.186	3.823	0.739
T8	0.000	0.025	0.186	0.607	0.182	4.152	0.656
T9	0.000	0.057	0.303	0.521	0.119	3.745	0.544

5. CONCLUSION

The article uses the reversible Flow model to extract the features of the photographic image, establishes the style migration model of photographic image realism, and designs the style migration and subjective evaluation experiments, so as to explore the effect of the intersection of painting and photography under the microscopic perspective.

(1) The style loss and the optimal transmission loss are set in the model, and the loss value of the model is stabilized at about 81.64 after 200 rounds of iteration, at which time it can obtain a style migration image that is more in line with the original photographic image, which can provide a source of inspirational mood for the creation of paintings.

(2) The PSNR and IS values of the model in this paper are 80.63 and 88.79, respectively, which are higher than the rest of the comparison models, and the FID value of the model is the lowest at 184.16, which is still 17.76% lower than that of the BiGAN model, which has the second best performance. The photographic style image generated by the model does not differ significantly from the original photographic image, which can truly reflect the compositional performance and spatial changes of the photographic image, and help create the picture space for painting creation.

(3) When the painting is created based on the images obtained by photorealistic image style migration, the comprehensive evaluation score of the painting work obtained is 4.075, and the similarity level with the original photographic image is high. Relying on the photographic realism image segmentation migration model can explore the color, spatial expressiveness and mood expression forms in the photographic image, making the painting creation better learning the spatial expression of the photographic image.

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