Application of Style Transfer Algorithm in Artistic Design Expression of Terrain Environment

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***Abstract*—The use of artistic expression to depict and express terrain and landform can not only convey terrain information, but also spread art and culture. The existing landscape design methods focus on the accurate expression of terrain height and the realistic expression of form, but neglect the aesthetic aspect of landscape design. In view of this situation, this paper studied the use of generative adversarial network, constructed the presentation mode of landscape plane style, and realized the expression of landscape art style. A terrain style transfer model based on a pre-trained deep neural network model and style transfer algorithm was constructed to achieve a variety of terrain style expressions. The results showed that, in terms of Peak Signal to Noise Ratio, the proposed style transfer algorithm was higher than style attention network and adaptive instance normalization, and the peak signal-to-noise ratio index value was increased by 7.5% and 16.5%. This indicated that the style transfer model proposed by the topographic artistry research had more advantages in terms of image diversity and fidelity. The Structural Similarity Index of the proposed algorithm has been greatly improved. This research expands the method of computer rendering of terrain environment art, which is of great significance for the preservation of traditional Chinese culture.**

Keywords*—Generative adversarial network; terrain; style transfer; artistic; peak signal-to-noise ratio; Structural Similarity Index

I. Introduction

Geographic abstraction is one of the important methods of geographical cognition. It is a key feature obtained by summarizing the geographical reality. There are two kinds of abstract processes on the basis of scientific cognition of topography: scientific abstraction and artistic abstraction [1-2]. Each of these topographic abstract processes has its own advantages and characteristics. Each formed a perfect and mature theoretical system, which can serve people's cognition of topographic landform. On the basis of terrain abstraction, the presentation of terrain expression is a problem worth studying. For a long time, domestic and foreign scholars have been committed to the quantitative and fine expression of terrain. The research on scientific and accurate expression of terrain has developed rapidly [3-4]. From hachure method, hill shading method, contour line method and other terrain three-dimensional scene construction, people can use computer to simulate the realistic terrain and ground objects. The scientific expression of terrain abstraction is becoming more and more mature. However, science and aesthetics are a pair of contradictory and unified contradictions. The aesthetic examination in science and the scientific connotation in aesthetics promote each other [5-6]. The existing research is more focused on the scientific and accurate expression of terrain, which cannot fully meet the diverse visual requirements of people. The study analyzes the representation of terrain through artistic expression by incorporating painting techniques to enhance the aesthetic quality of terrain representation. This research has significant implications for the study of artistic terrain representation. By using computer related technology, the expression technique of painting art with national characteristics is combined with the expression method of terrain to realize the artistic expression of terrain style. While enriching the terrain to express the cultural connotation, it can also make the reader feel the artistic charm of Chinese painting. Based on the in-depth study of terrain expression and artistic style learning, this paper first determines the extraction method suitable for terrain expression and forms the dataset of style samples. Then, a style transfer model oriented to terrain expression is constructed. Finally, the real terrain structural feature information is taken as the model transfer target to achieve the artistic expression of terrain style. This approach effectively integrates scientific and artistic expression of terrain expression. The research results are expected to enrich the content of terrain expression and improve the effect of artistic expression.

This study is mainly separated into the following six sections. Section II is a literature review on intelligent algorithms and style transfer applications. Section III is the construction of a style transfer model on the ground of generative adversarial networks (GAN). Section IV is an analysis of the algorithm performance and application results of the style transfer model proposed by the research institute. Results and discussion is given in Section V. Finally, Section VI concludes the paper.

II. Related Work

The research on traditional graphic art style can be roughly summarized into three categories: texture synthesis based on sample images, virtual brush model building based on strokes, and local separation processing based on image structure. Zhang and other scholars used GANs combined with attention mechanisms to convert real-world facial and cartoon style images into unpaired datasets. The results show that the proposed new model network avoids the complexity of the model and achieves a good balance in the task of style and content transformation [7]. Wang et al. proposed a cyclic consistent GAN on the ground of edge features and self attention for style transformation in visual effects. The model structure includes a generator, a discriminator, and an edge feature extraction network. The results show that the model has advantages in style conversion, as it can better preserve the details of the original image and has good image quality [8]. To promote the research on image style transfer on the ground of neural networks, Huang and other research teams summarized and discussed the main principles and methods of image style transfer on the ground of neural networks, and provided a detailed description of neural networks on the ground of neural networks [9]. Scholars such as Zhou proposed an image based convolutional neural network transfer model on the ground of deep mixing. This deep hybrid generation model mainly relies on the combination of adversarial network generation and self encoder [10]. Wei et al. proposed a transformation based visual style transfer method for rendering style patterns. The results indicate that under appropriate style supervision, the transformer can learn similar texture bias features like CNN [11]. Gupta and other research teams used transfer learning to pre train convolutional neural networks for image style transfer tasks. Using these models can generate high perceptual quality images, which are a combination of the content of any image and the appearance of famous artworks [12]. Kim and other scholars proposed a CNN inference accelerator for style transformation applications, which utilized network compression and layer chain technology. In addition, layer chain technology has been proposed to reduce off chip memory traffic, thereby increasing throughput at the cost of smaller hardware resources. The results show that this method has good performance in changing the style of content images [13].

In the field of environmental design, Yang and other scholars reviewed the development process of environmental art and design discipline, relevant key educational institutions, and the opinions of well-known scholars. In addition, in the context of emerging design trends, new collective and constructive environmental art design ideas and methods have also been proposed. Finally, this study suggests the uniqueness and regionality of design culture in the Chinese context through the study of the name dispute for environmental art design in China [14]. Scholar Wang conducted research on computer-assisted interaction of vision, elaborating on digital technology and its development trends in the future, and also pointing out that technology is the future practice of digital media art. It proposes a new form of art, which is the "intelligent visual art" that conforms to the development of the intelligent era, and explores the opportunities and challenges of intelligent visual art [15]. Liu and his research team conducted two user studies to evaluate the impact of three layouts with different curvatures around users in a virtual environment (flat wall, semi circular surround, and circular surround) on visual spatial memory tasks. The results show that compared to the circular layout, participants were able to recall spatial patterns more accurately and report more positive subjective ratings [16]. Liu and other scholars proposed a multi-dimensional urban landscape design method on the grounds of nonlinear theory to solve the problem of large differences in multi-dimensional urban landscape design. On the grounds of the parameterized model method, multi-dimensional nonlinear landscape design has been implemented, improving the quantitative analysis ability of multi-dimensional nonlinear landscape design [17]. Wang et al. proposed a virtual environment on the ground of virtual reality technology and intelligent algorithms, which uses a 3-bit binary to represent digital factors and creates a virtual environment by simulating the display environment. The research shows that applying virtual reality technology and intelligent algorithms to landscape design in coastal areas is feasible and has achieved certain results [18]. The purpose of research by scholars such as Thamrin is to achieve community service through collaborative design in interior design teaching. The article describes the learning and design methods on the ground of the human centered design method in collaborative design, and analyzes the benefits brought by this method [19].

In summary, there are currently many studies using convolutional neural networks or GANs to construct style transfer models for text or images. In the research of environmental artistic design, more pure theories or suggestions are presented, and less intelligent algorithms are introduced to achieve the artistic expression of terrain. In view of this, this study constructs a style transfer model for terrain artistic expression on the ground of GANs and two novel channel models.

III. Research on Style Transfer Algorithm for Terrain Representation

To address the issues of unsatisfactory performance of art attributes and incompatibility with style characteristics caused by image style conversion, this study aims to construct an image style conversion network that enhances art style attributes. On this basis, feature transfer and refinement of the two pathways are achieved through the attribute refinement pathway of the style domain and the semantic information refinement pathway of self attention. The former can highlight the aesthetic characteristics of the image, while the latter can combine the style characteristics of the image with its most suitable content characteristics on the grounds of the characteristics of the image. A pooling layer on the grounds of wavelet based multi-level decomposition has been introduced into the compiler of the generation algorithm, which maximizes the preservation of important features of the image during feature transfer. On this basis, a dual resolution discrimination network is used to distinguish different types of images, to obtain images similar to different types of images.

A. Extraction of Terrain Environmental Features

In the dissemination of style information, using a single channel style transformation branch is difficult to retain its unique style domain characteristics. This is mainly because after encoding the image content and style, there is no mapping between the semantic and style styles. However, using direct fusion during the decoding process will bring significant errors, which will prevent the decoding system from efficiently training attributes such as color and texture. This can reduce the decoding system's ability to extract deep style features, ultimately resulting in changes in the strokes in the generated graphics, i.e. missing attributes in the style domain. In response to the requirement to focus on style domain attributes in style conversion, this study proposes to use region perceptrons as the extraction channel for style domain attributes. On the grounds of a comprehensive analysis of texture characteristics, high-precision extraction in the style domain is achieved and converted into style domain attributes. Fig. 1 is a schematic diagram of the style domain attribute refinement channel.

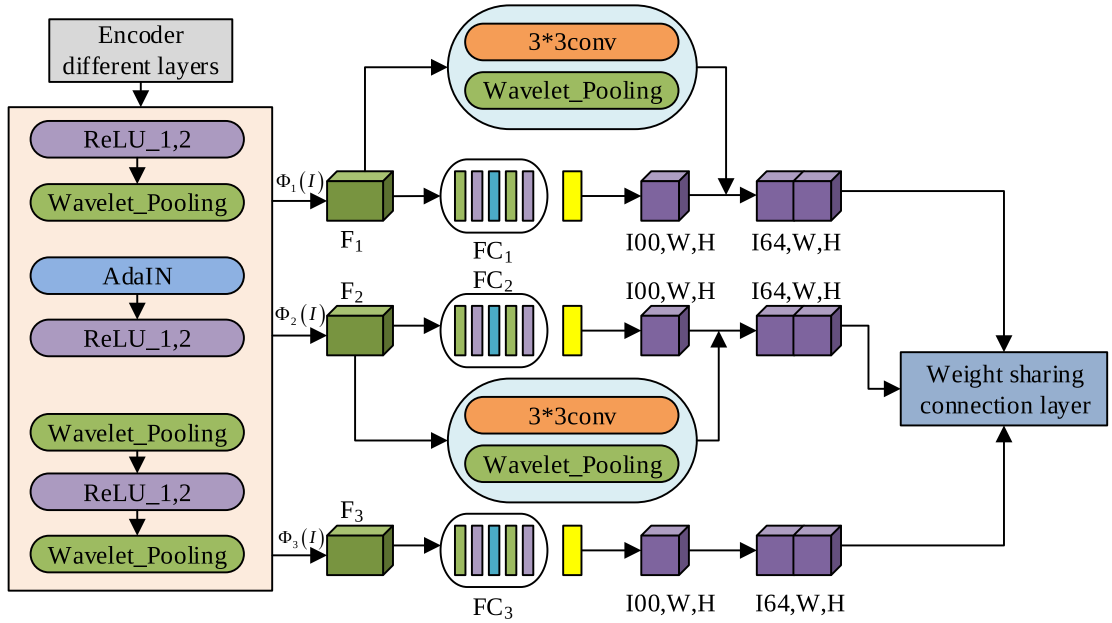


Fig. 1. Style domain attribute refinement channel.

It obtains image feature maps at different levels through encoders at different levels, and obtains texture and color information of the image through the Gram matrix. In the process of encoding the style, the feature maps of different levels are segmented into multiple channels through 3x3 convolution, and then wavelet fusion operation is added to obtain the feature maps of the channel set, thereby avoiding the loss of local parameters without increasing the size of the feature maps. Finally, a style feature map on the ground of channel sets is constructed, and a weighted convolution method is used for forward diffusion to obtain the style domain attributes of each level, thereby achieving complete migration and accurate fusion. Eq. (1) is the calculation expression for the feature map.

$$F_i^{DI} = h\left(\left[FC_i\left(Gram\left(F_i\right)\right) \otimes F_i'\right]\right) \quad (1)$$

In Eq. (1), F_i represents the feature maps obtained from different layers. F_i' represents the channel set feature map. α_i represents the style domain attribute. $\otimes$ represents the channel connection operator. FC is the fully connected layer. h is the weight sharing fully connected layer. Eq. (2) calculates an expression for the style domain attribute.

$$\alpha_i = \sigma\left(F_i^{DI}\left(I\right)\right) \quad (2)$$

In Eq. (2), σ represents the sigmoid operation.By refining the attributes of the style domain between the modules that compile the style image, a communication bridge is established to match similar types of features, thus achieving a direct transfer of style domain attributes. This reduces the error of style feature transfer and solves the problem of generating style images without style domain attributes. Meanwhile, through this new approach, the instability of overall feature transfer is enhanced, and the overall style information such as color and texture is effectively integrated to achieve overall style transfer, thereby achieving a more harmonious visual effect. Due to the significant regional distribution characteristics of patterns and the differences in style domain information displayed by different regions, it is necessary to achieve synchronous maintenance of the overall and local styles, and to adaptively adjust the constructed neural network to achieve automatic matching of the most consistent style features. This method utilizes a self attention mechanism to train the regularized model, and improves it to have higher credibility and average accuracy. This is to achieve accurate matching of images with the same semantics in type images. This is precisely in line with the process of image migration, which involves matching the content contained in the image with the semantic information contained in the image to achieve the closest possible style transfer. Fig. 2 shows the self attention semantic feature matching channel.

Using factor decomposition paradigm standardization, standardized text information and style information are obtained as input through self focused semantic feature matching channels. On this basis, the study extracted the semantic consistency between the two and their key features, thus achieving the learning of standardized parameters. This method can achieve dynamic pixel by pixel shift and scaling of content features, while maintaining content features to match the style characteristics of the text. The conversion process can be expressed by Eq. (3).

$$\overline{F_c'}, \overline{F_s'} = \gamma_s \otimes \left(\alpha_{c\_s}\left(\overline{F_c}, \overline{F_s}\right) + \alpha_{c\_s}\right) + \beta_s \quad (3)$$

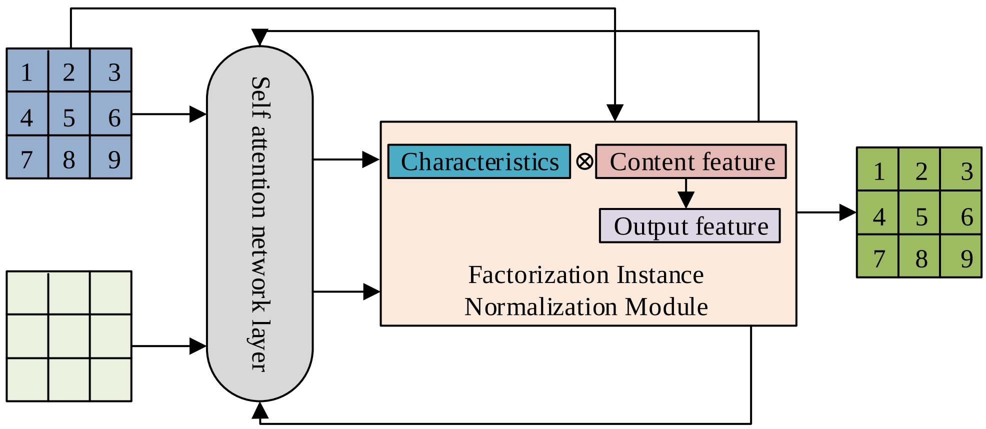


Fig. 2. Self attention semantic feature matching channel.

In Eq. (3), γ_s and β_s represent normalization parameters respectively. $\overline{F_c}$ and $\overline{F_s}$ represent normalized content and style features, respectively. $\overline{F_c}', \overline{F_s}'$ represent the content and style features refined by the self attention semantic feature matching channel. α_{c_s} and α_{s_c} are unit vectors along the channel dimension, which obtain standardized content and transition information between styles before style matching. Eq. (4) represents the normalization parameter calculation formula.

$$\begin{cases} \gamma_s = ReLU\left(conv_{1\times1} \otimes SA_\gamma\left(\overline{F_c}, \overline{F_s}\right)\right) \\ \beta_s = ReLU\left(conv_{1\times1} \otimes SA_\beta\left(\overline{F_c}, \overline{F_s}\right)\right) \end{cases} \tag{4}$$

SA_γ and SA_β represent self attention convolutional network layers.

B. Construction of Style Transfer Model

On the grounds of the GAN, a picture style transmission mode was established to enhance artistic style attributes. The function of the generator is to take content images and style images as inputs, responsible for representing mapping relationships and obtaining the generated images [20]. Discriminator is a dual resolution discriminator network that can distinguish between original and newly created images by using the original image as the correct sample and the generated image as the error sample. Fig. 3 is a schematic diagram of the generator structure.

This study proposes a generator network consisting of an encoder, a dual channel characteristic transmission module, and a decoder. The dual channel feature transmission module consists of two parts: one is the type field attribute refinement path. The other part is the self attention path. On the grounds of content images and style images as inputs, novel style images are created through the structural features of content images and the style features of style images. In addition, to maintain the edge features and style features of the content image, a new pooling layer has been introduced in the codec, as shown in Fig. 4.

The wavelet multi-layer transformation network decomposes feature maps at multiple levels, achieving effective extraction of feature maps in high and low frequency bands. In the image, the parts with high color impact exhibit a stepped change in grayscale, which best displays the details of the image and is also a characteristic of the image. On this basis, the high-frequency sub band information in the region is matched with it, and then synthesized into a feature band, which is then converted into a sub feature band by the excitation function of the band. For the background area of the image, its grayscale distribution is within a certain range, and the differences in values are not significant, occupying the largest part of the entire image area. It represents the low-frequency subbands of the image, which can be used as the input for each level of filter. Eq. (5) is the mathematical expression for this process.

$$\{LL, LH, HL, HH\} = F_{DWT}(LL) \tag{5}$$

In Eq. (5), (HH, LH, HL) represents high-frequency subband information. LL represents low-frequency subband information. f_1 represents the feature map. F_{DWT} represents the filter operation of wavelet transform. Eq. (6) is the calculation ratio expression for feature map f_1.

$$f_1 = ReLU\left(BN\left(Conv_{3\times3}(LH, HL, HH)\right)\right) \tag{6}$$

In the reconstruction step, it reverses the decomposition step by upsampling the sub feature maps, then convolves them with a filter to obtain the sub feature maps, and finally obtains the reconstructed feature maps. Finally, this information is input into the encoder/decoder for the next step of feature extraction. Fig. 5 shows the discriminator network structure.

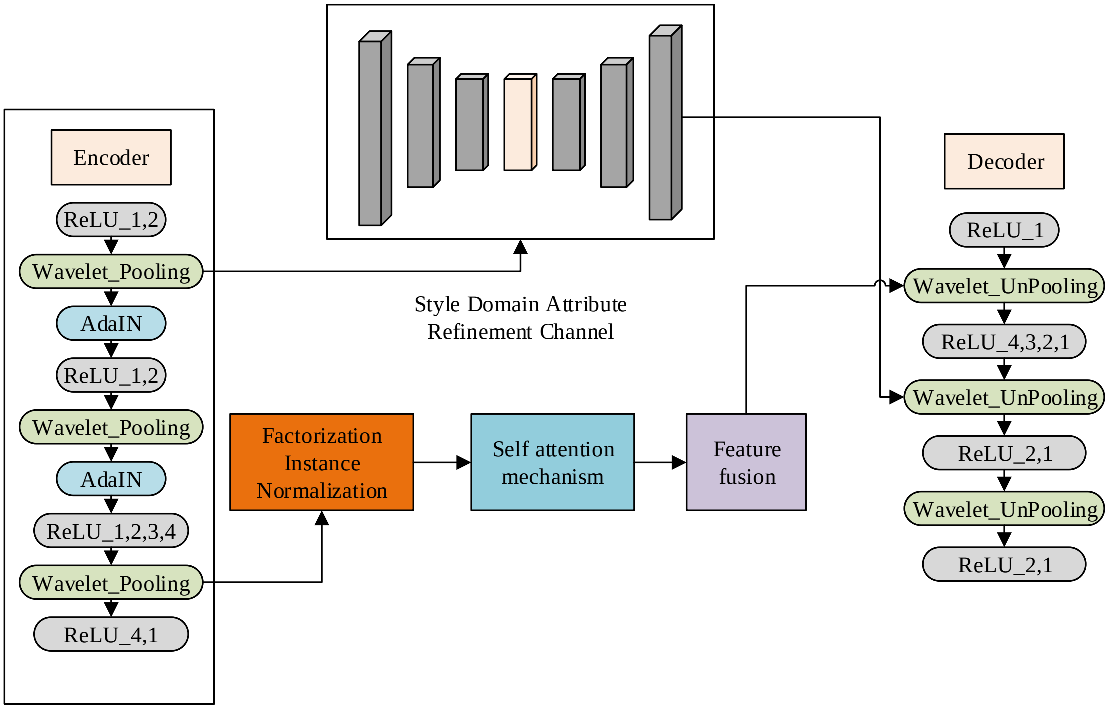


Fig. 3. Schematic diagram of generator structure.

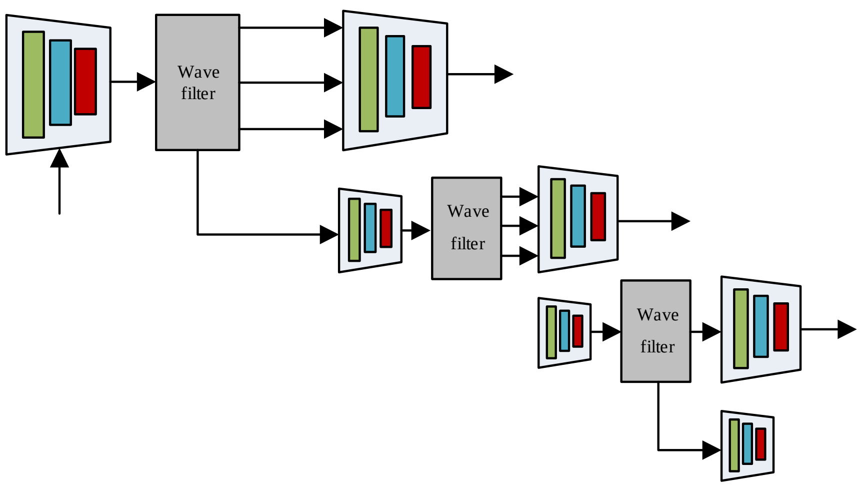


Fig. 4. Pooling layer based on wavelet multilevel transform.

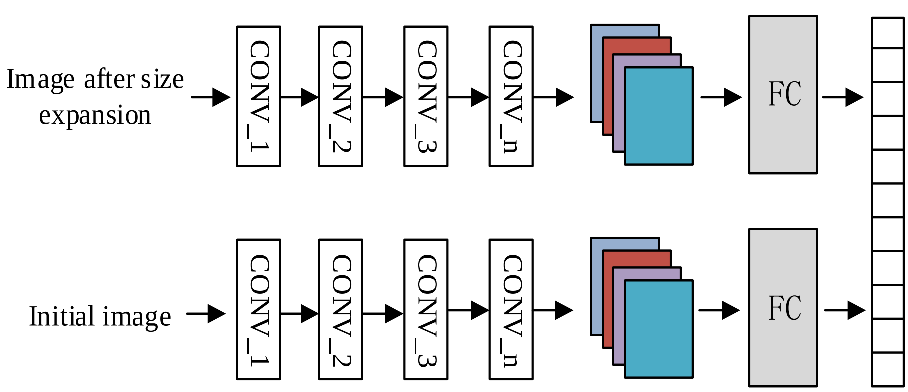


Fig. 5. Discriminator network structure.

The discriminator adopts a dual resolution type, which distinguishes the generated images by combining high-definition discriminators with traditional ones. The high-definition discriminator first enlarges the image to 512x512, and then inputs the configuration of the discriminator into the discriminator. Improved resolution allows for better capturing of textures in images. Its main goal is to obtain more realistic images by imposing more restrictions on the high-resolution characteristics of the images. Traditional resolution discriminators can effectively constrain the global structure of the generated image and ensure the semantic correlation between images, thereby improving the quality of the image. Eq. (7) is the loss function of GAN network, style domain attribute transformation network, and feature transformation module.

$$L_{AAH-GAN} = E_x\left[InD\left(I_s\right)\right] + E_z\left[In\left(1-D\left(G\left(I_c\right)\right)\right)\right] + L_{DI} + L_{SAFIN} \quad (7)$$

In Eq. (7), $G\left(I_c\right)$ represents the generated stylized image. $D\left(I_s\right)$ represents the probability that the input image will be judged as true. $D\left(G\left(I_c\right)\right)$ represents the probability that the stylized image given by the discriminator is a real image. L_{DI} represents the loss of style domain attribute refinement channels. L_{SAFIN} represents the loss of self attention semantic feature matching channel. Eq. (8) refines the channel loss function expression for style domain attributes.

$$L_{DI} = \lambda_{bce}L_{bce} + \lambda_{dlow}L_{dlow} \quad (8)$$

In Eq. (8), L_{bce} represents domain attribute loss. L_{dlow} represents the loss of feature fusion process. λ_{bce}, λ_{dlow} represent the weighting factor for domain attribute loss and feature fusion process loss. Eq. (9) is the fusion feature calculation formula.

$$I_{mix} = mix\left(F_{S_c}, F_{S_s}, \beta\right) \quad (9)$$

In Eq. (9), I_{mix} represents the fused features. *mix* represents the Mixup method. β represents the interpolation strength. Eq. (10) is the calculation formula for the channel loss function of self attention semantic feature matching.

$$L_{SAFIN} = L_c + \lambda_s * L_s \quad (10)$$

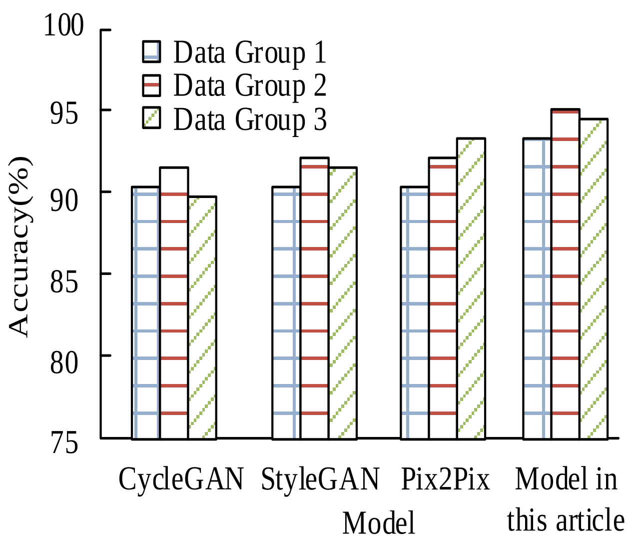
In Eq. (10), L_c and L_s represent loss of content and style. λ_s represents the weight coefficient assigned to style loss relative to content loss.

IV. Utility Analysis of Improving GAN's Terrain Artistic Style Transfer Model

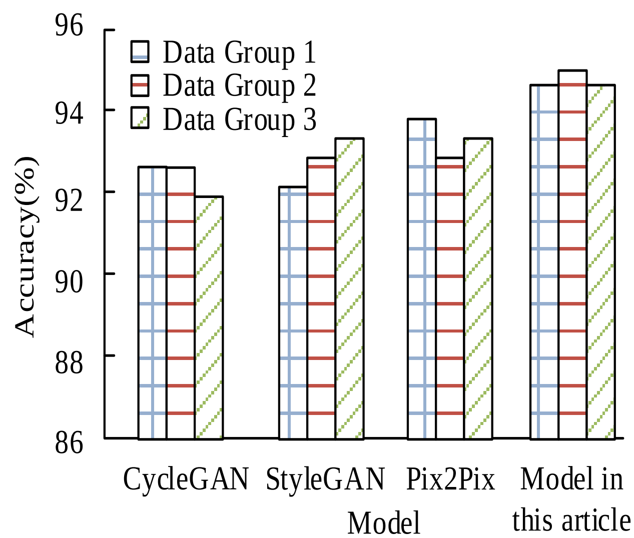
To verify the effectiveness of the GAN style transfer model on the grounds of dual channel improvement proposed by the research institute, this study divided the experiment into performance verification and application effect verification stages. Performance testing mainly evaluates the algorithm itself, while the application effect is related to the style transfer of terrain images.

A. *Performance Analysis of Style Transfer Model on the Ground of Dual Channel Improved GAN*

The system used in the experiment was UBUNTU-18_ cuda10.1, which was accelerated using two Ge ForceRTX2080 Ti chips. On this basis, an Adam optimizer was used with a learning rate of 0.0001 and an iteration number of 2000 as initial parameters. The dataset contains 6000 Impressionist images, all of which can be resized to 256x256, and any size image can be used during the testing period. The comparative algorithms used in the study are CycleGAN, StyleGAN, and Pix2Pix. The evaluation indicators are accuracy, recall, and F1 value.



(a) Accuracy results of different models on the test set

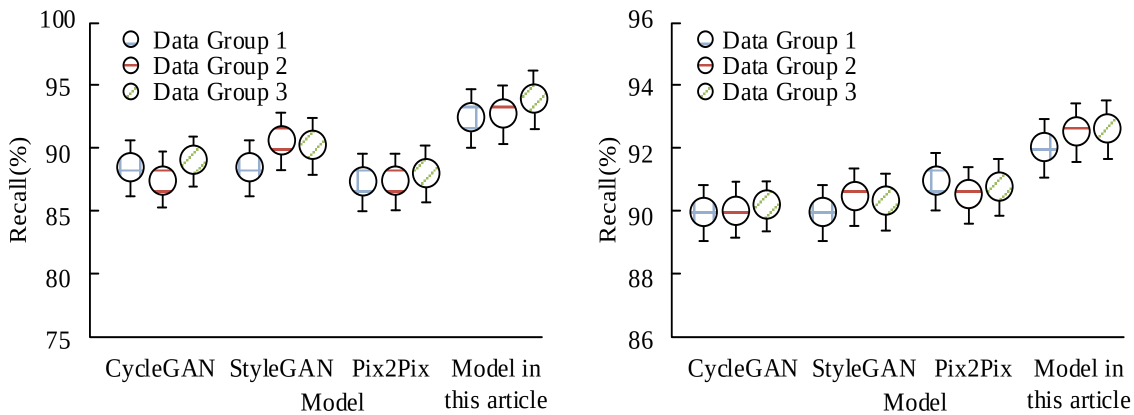


(b) Accuracy results of different models on the training set

Fig. 6. Accuracy bar chart.

Fig. 6 (a) shows the training results of the model on the test set, the proposed model in the study achieved the highest accuracy values, corresponding to the accuracy results of 93.8%, 95.1%, and 94.6% for the three data groups, respectively. Fig. 6 (b) shows the training results of the model on the training set. The StyleGAN and Pix2Pix algorithms have the highest accuracy of 92.8% and 93.7% on the three data sets. This indicates that the highest accuracy of the model proposed in the study has been improved by 2.3% and 1.4%, respectively, compared to the latter two algorithms.

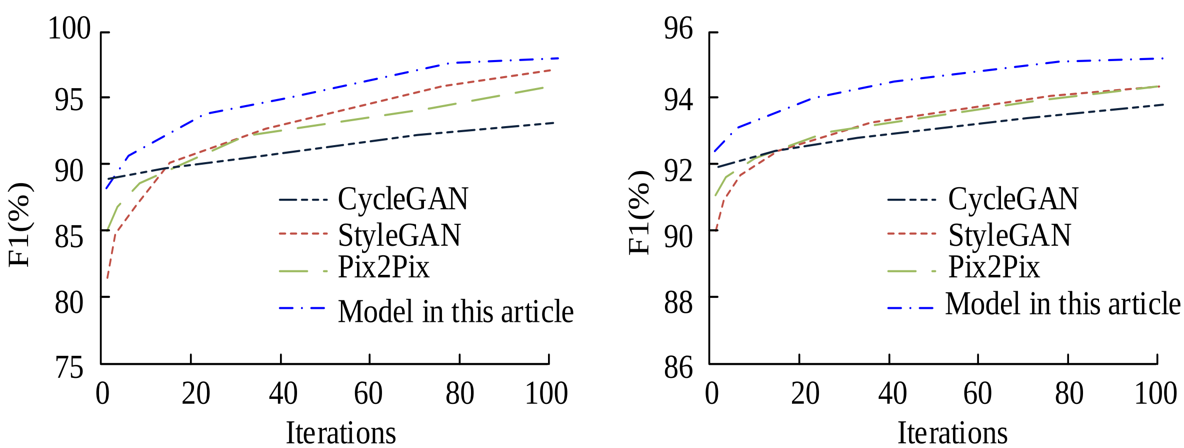
Fig. 7 (a) and Fig. 7(b) show that the proposed algorithm has the highest recall rate on both the test and training sets. On the test set, the recall rates of the models proposed by the research institute are all above 90%, with a maximum value of 94.6%, while the highest recall rates corresponding to StyleGAN and Pix2Pix algorithms are 90.2% and 87.4%, respectively. By comparison, it can be seen that the algorithm proposed by the research institute has improved the recall rate by 4.4% and 7.2%.



(a) Recall results of different models on the test set

(b) Recall results of different models on the training set

Fig. 7. Recall rate box plot.



(a) Training set

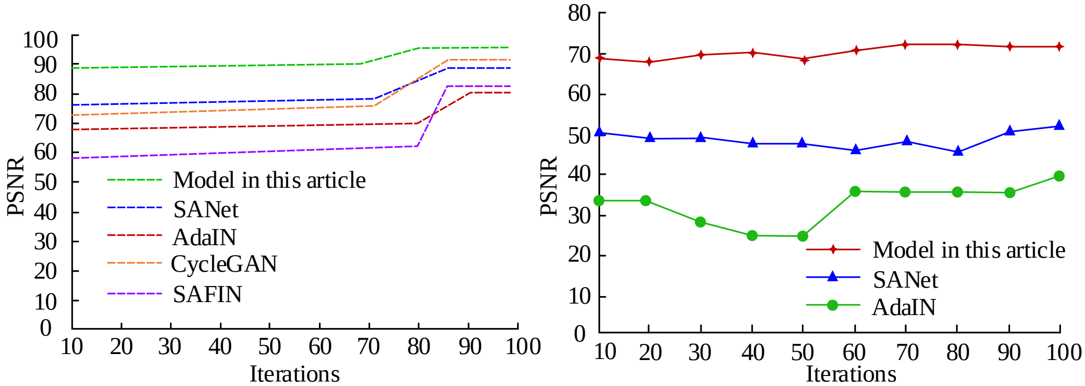
(b) Test set

Fig. 8. F1 value line chart.

Fig. 8 shows that the model proposed in the study is at its highest position on the F1 value curve. Fig. 8 (a) shows the training results of the model on the test set, when the number of iterations is 100, the F1 value converges to 97.6%, which is 2.3% higher than the StyleGAN algorithm. Fig. 8 (b) shows the training results of the model on the training set, when the iteration is completed, the F1 value of the proposed algorithm converges to 95.3%, which is higher than 95%.

B. Analysis of the Application Results of Style Transfer Model Based on Dual Channel Improved GAN

The experimental dataset remains unchanged, and the comparative algorithms used in the study are Adaptive Instance Normalization (AdaIN), Style Attention Network (SANet), CycleGAN, and SAFIN. Using Peak Signal to Noise Ratio (PSNR) to measure the distortion state, the size of PSNR reflects the similarity between the migrated image and the reference. The Structural Similarity Index (SSIM) parameter is used to measure the similarity between the content image and the generated image. The closer SSIM is to 1, the more similar the structure is. Using IS scores to evaluate the clarity and diversity of generated images, the higher the IS score, the better the quality of the generated images. Fig. 9 shows the PSNR curves of different algorithms.

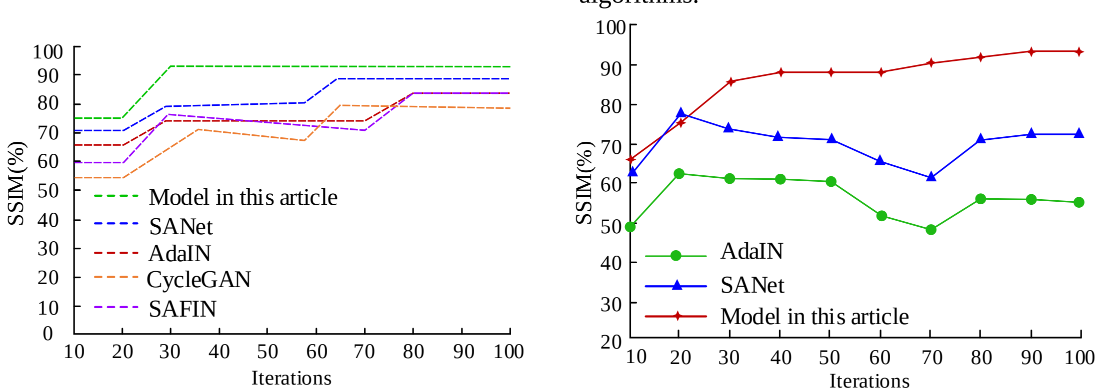


(a) Training set (b) Test set

Fig. 9. PSNR curves of different algorithms.

Fig. 9 (a) shows that the PSNR curves of the images obtained from the training dataset exhibit consistency, all gradually increasing and tending to converge. As the iteration process progressed, the proposed algorithm achieved the highest PSNR index value of 95.9 when the number of iterations was 80. The SANet algorithm achieved a second highest PSNR index value of 88.7 when the number of iterations was 85. The AdaIN algorithm achieves a minimum PSNR metric value of 80 when the number of iterations is 90. By comparison, it can be seen that the algorithm proposed in the study achieved the fastest convergence speed and the highest PSNR index value, which were 7.2 and 15.9 higher than the latter, respectively. Fig. 9 (b) shows that the proposed algorithm achieved the highest PSNR index value in the test set, with a size of 71.8, and the overall PSNR curve remained around 70 with minimal fluctuations. The overall PSNR index value of the SANet algorithm fluctuates around 50. When the iteration reaches the middle and late stages, the curve fluctuation increases. When the iteration number is 100, the PSNR index value is 52.6, which is 19.2 lower than the model proposed in the study. The PSNR value curve of AdaIN algorithm is at its lowest point throughout the entire iteration time, and there is a certain downward trend in the early stages of the iteration. The final PSNR value is 40.

Fig. 10 (a) shows that on the training set, the algorithm proposed in the study is closest to 1 in terms of SSIM index. At the end of the iteration, the corresponding SSIM index value is 92.5%. And the curve begins to converge when the number of iterations is 30, with almost no fluctuations in the convergence process and excellent convergence performance. The SSIM index curves corresponding to the SANet algorithm and AdaIN algorithm both have two climbing processes, with 64 and 80 iterations starting to converge, both of which are higher than the algorithm proposed in the study. In terms of SSIM convergence value, the SSIM values of the latter two algorithms are 89.9% and 82.6%, which are reduced by 2.6% and 9.9% compared to the algorithm proposed in the study. Fig. 10 (b) shows that on the test set, the SSIM index curve of the proposed algorithm in the study shows a continuous climbing trend, with a relatively smooth upward process and no falling curve segments. When the number of iterations is 100, the SSIM index value of this curve is 93.6%, which is higher than 90.0%. The SSIM curves of the SANet algorithm and AdaIN algorithm both show a downward trend during the iteration process, and the overall SSIM index values are both below 80%. At the completion of the iteration, the SSIM index values of the two algorithms were 72.8% and 55.6%, respectively. By comparison, it can be seen that the SSIM index values of the algorithm proposed in the study have increased by 20.8% and 38% compared to the latter two algorithms.



(a) Training set (b) Test set

Fig. 10. Different algorithm SSIM curves.

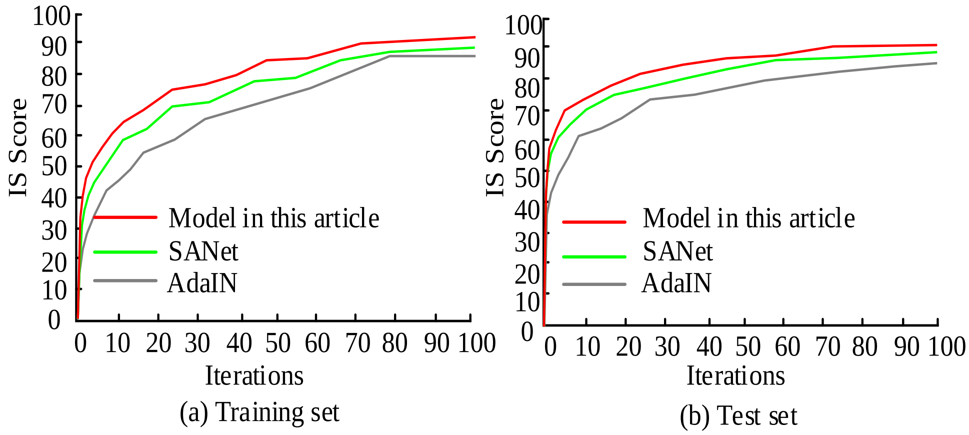


Fig. 11. Different algorithm IS curves.

Fig. 11 (a) and Fig. 11 (b) show that the IS score curves of the three algorithms show the same trend of change, with a slow upward trend in fluctuations, regardless of whether it is the training set or the test set. Among them, the IS score of the algorithm proposed in the study has always been at the highest level during the iteration. When the number of iterations is 100, the IS scores on both datasets are 91.8% and 90.0%, while the AdaIN and SANet algorithms have IS scores below 90% on the training set and test set. By comparison, it can be seen that the algorithm proposed in the study has a higher IS score, indicating that the algorithm proposed in the study has a more naive clarity and diversity in image transfer.

V. Results and Discussion

The expression of terrain art features is subjective and complex, making it challenging to use existing art style learning algorithms for style rendering. In this paper, a deep convolutional neural network for distinguishing and extracting stylistic texture features is designed based on a pre-trained deep neural network model. A sample feature dataset containing different styles is made, which is used to train the network. Combined with the idea of style transfer algorithm, a terrain style transfer model is constructed based on deep neural network to realize the expression of multiple styles of terrain. Based on the observation of various scenes, different styles of terrain expression can be perceived. The experimental results show that the proposed method has the following characteristics: 1) The terrain style transfer model can generate different styles of terrain representation by adjusting content reconstruction and style reconstruction factors. 2) The model is suitable for the style rendering of a large range of terrain scenes. 3) It can realize the artistic expression of terrain ink painting style from multiple perspectives.

Terrain style expression is a form of terrain artistic expression that involves scientific cognition, artistic abstraction and artistic expression. It requires a balance between science and art. The results of the topographic expression of style were evaluated from the aspects of science and aesthetics. On the one hand, the validity of the result of terrain artistic expression is evaluated qualitatively. The results show that the topographic style transfer results generated by the research extraction method can take into account the scientific expression (the maintenance of the topographic feature structure) and the artistic expression (the aesthetic expression of the style). The number of topographic feature elements affects the overall effect of topographic style transfer. The extracted topographic feature elements are too few or too many, and cannot show a good effect. Through the evaluation of multiple style renderings, it is shown that the result of the combination of multiple convolutional layers in a deep neural network produces better results in expressing the style image, resulting in a smoother and more continuous visual experience. On the other hand, using texture analysis method for reference, the transfer effect of style texture is quantitatively analyzed. It is found that the general trend of each texture feature parameter curve is similar to the style sample, which indicates that the model can accurately realize the transfer of multiple styles. The migration degree of style texture in the model is different in four aspects: the ranking from high to bottom is manifested as obvious degree > complexity degree > similarity degree > thickness degree.

VI. Conclusion

Combining the expressive techniques of graphic art with the expressive techniques of landforms can enhance the beauty of landforms, thereby enriching their artistic expression. To achieve the artistic expression of the terrain landscape, this study was on the grounds of generating adversarial networks and establishing a new style transfer mode. This pattern included two channels: attribute refinement in the style domain and self-focused semantic feature matching. It utilized the pooling layer of wavelet multi-level transformation to preserve the boundary and style characteristics of the content image. The results showed that in terms of SSIM indicators, the corresponding value of the model was closer to 1, and the convergence value of SSIM was 0.925. The SSIM convergence values of the other two algorithms were 0.899 and 0.826, both of which are below 0.9. The algorithm proposed by the research institute exhibited the same iterative trend in IS score indicators as AdaIN and SANet algorithms. However, in the process of change, the model proposed by the research had a higher IS score, with an IS score of 91.8% at the completion of the iteration. This indicated that the terrain artistic style transfer model proposed by the research institute had more advantages in presenting image clarity and richness.

Therefore, this model had certain application potential in reconstructing style content for artistic expression of terrain. The scientificity was an important factor to evaluate the result of the style expression of terrain ink painting. However, this paper only provided a qualitative measurement. In the future, on the basis of this study, it is necessary to deeply analyze the results of topographic ink style transfer, and put forward a quantitative analysis method of topographic information preservation.

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