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Computer-Aided Design AND APPLICATIONS

The Implementation Path of New Media Art Design Integrating Deep Learning Style Transfer and CAD Interaction Technology

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Abstract. The transformation of artistic style image features is a major challenge in the current computer training process. The traditional method is to apply neural network models to new image videos for transfer. To address the issue of style characteristics in traditional methods. This article explores deep learning under the integration of art-style interaction technology in new media. Through the construction of neural network models for deep learning, this article has achieved efficient style transfer and style transfer transformation for CAD technology. In the process of style transformation in interactive technology, this article explores the real-time process monitoring and adjustment of convolutional neural network models. This not only increases the inherent style transfer accuracy but also greatly enhances the efficiency level of artistic images in the feature extraction process. This method has played a significant role in improving style conversion. The results showed that the F1 score increased by 10% in the comparison process of different methods. Therefore, in the foreseeable future, this method can be applied more efficiently.

Keywords: Deep Learning; CAD; Style Transfer; New Media Art; Interactive Technology
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1 INTRODUCTION

With the rapid expansion of the digital media industry, the content and structure of the industries involved have changed, and the demand for digital media talents will inevitably change accordingly. By fully understanding the connotation and application performance of digital media art and conducting in-depth analysis and comparison of the development of the digital media industry at home and abroad [1]. Especially with the advent of the knowledge economy and the unprecedented development of the digital media industry, higher demands have been placed on talent in terms of both quantity and quality. Combining the differences and changes between traditional industries and digital media industries, correctly grasping the demand for digital media talents after industrial structure adjustment, and identifying the current problems in digital media art education [2]. Explore effective ways to cultivate digital media art talents that meet the current needs of the digital media industry, and ultimately envision new trends in digital media art under the influence of artificial intelligence [3]. Therefore, cultivating the necessary professional talents is an important part of the restructuring of the digital media industry. Secondly, contemporary art media needs to enhance column specialization and content personalization and strengthen originality and topic extension. A new media thinking approach needs to be established based on aesthetics, evaluation, and screening of art itself and requires intervention [4]. The new media communication of contemporary art exhibitions is located in a brand new work environment, not just by setting up a simple live broadcast camera or news from paper media. At the same time, less academically obscure language and plain, vivid, and interesting language are the textual foundations for enhancing public understanding. Humanities and value judgments are included in artistic symbols, which inevitably requires art media to achieve a balance between market and academia [5]. These features can capture subtle changes in tone, speed, volume, and other aspects of speech, thereby revealing the emotional state hidden behind the speech. The final emotional state is determined by the output of both speech and text sentiment analysis, and this multimodal fusion approach makes our model more widely applicable in new media art design. The experimental results show that the overall recognition accuracy of the text is improved by 6.70% compared with the single mode, and the accuracy of speech emotion recognition is increased by 13.85%. By accurately identifying the emotional state in artistic works, it can provide audiences with a more personalized artistic experience, and enhance the infectivity and attractiveness of artistic works [6].

However, relying solely on deep learning style transfer technology is not enough to meet all the needs of new media art design. In the actual creative process, artists need to interact and modify their works in depth to achieve the best artistic effect. At this time, CAD interactive technology is particularly important. As a mature CAD tool, CAD technology has powerful modeling, rendering, and editing functions, which can help artists control and adjust the details and effects of their works more accurately. Through CAD interactive technology, artists can easily realize visual previews, real-time modification, and efficient collaboration with their works, thus greatly improving the efficiency and quality of creation. In the field of new media art and design, music is not only an auditory experience but also an interweaving of vision, sensation, and cognition [7]. It utilizes ski hill diagrams and loop diagrams, two tools derived from mathematical music theory, to visualize the evolution of Western music theory, enabling the audience to intuitively understand the expression of rhythm, rhythm, and pitch in music. Especially when dealing with non-symbolic music like music, psychoacoustic methods are particularly important. However, through psychoacoustic methods, we can more accurately capture and analyze the characteristics of Ibo music, such as melody, rhythm, and timbre, providing strong support for its preservation and academic discussions. By using psychoacoustic methods and visual tools such as ski hill diagrams and loop diagrams, we aim to demonstrate the theory of rhythm and explore its application in new media art design [8]. To deepen the audience's understanding of the relationship between music and mathematics, especially their forms of expression in new media art. The fairness, authenticity, and independence of artistic information in the dissemination process still need to be controlled. Research has found that art media have more press releases and fewer specialized articles. The fundamental difference between art media and commercial advertising lies in the experiential and interactive multimedia channels. Even under limited thematic coverage, media content arranged for publication involving promotional expenses and exchange cooperation affects the independent perspective of art criticism. By perfectly combining digital media technology with art, new media interactive installation art has become a new form of art [9]. At the same time, its media, the relationship between authors and readers, and the way it experiences texts have undergone unprecedented changes, which makes new media interactive installation art have unique aesthetic characteristics. New media interactive installation art is different from traditional art forms. Due to the use of multiple media, it brings infinite possibilities for the creative and expressive forms of new media interactive installation art.

However, it is not easy to realize this fusion technology. First of all, deep learning style transfer technology and CAD interactive technology belong to different technical fields, which need cross-disciplinary knowledge reserve and technical support. Secondly, merging these two technologies poses several technical obstacles, including ensuring the precision and naturalness of style transfer, as well as enhancing the user experience of the CAD interactive interface. To overcome these obstacles, this article presents a realization path for new media art design that seamlessly integrates deep learning style transfer with CAD interactive technology [10]. Initially, the article clarifies the fundamental concepts and tenets of both deep learning style transfer and CAD interactive technology while also scrutinizing their respective strengths, weaknesses, and current application status. Then, the necessity and feasibility of fusion technology are discussed, and the overall framework of fusion technology is put forward. Then, the implementation steps and methods of fusion technology are introduced, including the construction of a style transfer model and the integration of style transfer and CAD interaction. Finally, this article verifies the actual effect of the fusion technology through specific case analysis and practical exploration. Music emotion recognition plays a crucial role in new media art design. It is not only the core technology of music information retrieval but also a bridge connecting music and audience emotions. This model is based on the powerful capabilities of convolutional neural networks and recurrent neural networks and can adaptively learn sequence information of significantly influential features (SII-ASF) from the two-dimensional time-frequency representation (i.e., spectrogram) of music audio signals. This method cleverly transforms the regression prediction process into a weighted combination of multiple binary classification problems, significantly reducing training time and improving prediction accuracy. Meanwhile, a large number of experiments have also shown that the method proposed in this article is superior to state-of-the-art methods in the field of music emotion recognition. In addition, the extracted SII-ASF is not only robust to changes in genre, timbre, and noise but also highly sensitive to emotional changes. The experimental results show that the WHBR method can significantly reduce training time and improve prediction accuracy. This achievement not only brings breakthroughs to the field of music information retrieval but also injects new vitality into the development of new media art and design.

Through the exploration of this article, I hope to contribute to the development of new media art design and promote the progress of new media art design. The research has the following innovations:

(1) This article discusses the optimization methods of deep learning style transfer technology, such as real-time style transfer and case normalization technology, which improves the performance of style transfer.

(2) This article expounds on the important role of CAD technology in art design, including modelling, rendering and editing, which provides a powerful creative tool for artists.

(3) This article introduces a novel concept of integrating deep learning style transfer technology with CAD technology, exploring the potential application value of this merged technology in the field of art design.

(4) The article presents the utilization of a CNN-based deep learning framework for image style transfer, demonstrating the impact of these technologies on artistic creation styles.

2 RELATED WORK

With the flourishing development of new media art, the role of computer graphics in assisting art design is becoming increasingly prominent. New media art and design, as an innovative form that integrates traditional art and modern technology, cannot be taught and practiced without the support of computer graphics and digital image technology. In the process of computer graphics and image-assisted art design, special attention should be paid to how to use modern computer design methods to create an efficient and practical computer-aided design platform system. Based on the characteristics of new media art and design, a modular decomposition method is adopted to simulate and implement the entire process of art and design on a computer. Pei and Wang [11] developed a strategy for using digital means to establish sensory interactive teaching methods. In new media art design, spatial form theory is an important component. This includes not only software selection and development but also hardware upgrades and configurations, as well as integration and optimization of network resources. Meanwhile, digital design experience methods can effectively cultivate students' modelling and aesthetic judgment abilities, enabling them to continuously explore and innovate in design practice. Through digital means, we can transform abstract spatial form theories into intuitive visual images, allowing students to perceive and understand them in practice. In the new educational environment, how to effectively integrate online teaching resources and build a new media art and design teaching platform centred on digital content innovation has become the key to improving teaching quality. Through this study, it is expected to promote the teaching concepts of digital computer graphics and image-assisted art design. Pelliccia et al. [12] integrated digital teaching and training methods into the daily teaching of new media art design. This not only helps to improve the quality of teaching but also provides students with a more intuitive and vivid learning experience, helping them better understand and master the core knowledge and skills of new media art and design.

With the rapid development of computer technology, its application in the field of art is becoming increasingly widespread, especially in new media art design, where computer technology has become an indispensable auxiliary tool. At the same time, the application of computer technology has also made teaching content richer and more vivid, improving students' interest and participation in learning. Digital media art relies on digital media technology to showcase creativity, which has a profound and crucial impact on the development and growth of the cultural and creative industry. Countries around the world focus on the economic benefits brought by the cultural and creative industry. To understand the digital transformation brought about by digital media art in the era of artificial intelligence and to explore the characteristics and future development of digital media art. Then, from the perspectives of technology, communication, and art, observe the current performance of digital media art at the increasingly intelligent level and identify the hidden problems and response methods under the wave of intelligence. Have a clear concept of digital media technology and a general understanding of the application scenarios of digital media technology in the era of intelligence. Reflecting on innovative development strategies for digital media art, analyzing the digital media industry, and conducting relevant talent cultivation thinking on the new talent demand brought about by the growth and development of the digital media industry. Therefore, Zhang and Rui [13] clarified the concepts of digital media and digital media art through academic research by domestic and foreign scholars and understood the relationship between digital media technology and artificial intelligence.

With the widespread dissemination and application of information technology, the field of new media art and design has also ushered in unprecedented development opportunities. The rise of new media art and design not only enriches the forms of artistic expression but also promotes the diversified development of the art field. The challenge of new media art design to educational models is mainly reflected in its interdisciplinary and innovative nature. Secondly, the inadequacy of the knowledge construction system is another issue in new media art and design education. Therefore, we need to establish an open, flexible, and diverse education model to meet the development needs of new media art and design. To address this issue, Zhang and Yi [14] continuously update and improve our knowledge system and introduce the latest technologies and theories into teaching. Finally, the aging of course content is also a concern for new media art and design education. In the context of new media art and design, traditional art and design education are facing enormous challenges and changes. However, the current education system often lags behind the development of industries in terms of knowledge construction, leading to a disconnect between the knowledge learned by students and the actual work needs. On the other hand, new media art design integrates various technologies and art forms, requiring educators to have interdisciplinary perspectives and innovative abilities. Based on the current situation of new media art and design education, Zhu [15] analyzed its impact and existing problems on contemporary art and design teaching. With the continuous updates and upgrades of new media technology, related knowledge and skills are also constantly changing. Traditional art and design courses often focus on imparting basic knowledge and skills, while neglecting the cultivation of students' innovative thinking and creativity. Currently, new media art and design education is in a critical adjustment stage. To adapt to the rapid development of new media art and design, the education system needs to be constantly updated and improved.

3 OVERVIEW OF DEEP LEARNING STYLE TRANSFER TECHNOLOGY

The fundamental principle behind deep learning style transfer technology involves training a deep neural network to simultaneously learn and distinguish between the content and style of an image. The difference between images and digital images is reflected in the aesthetic and conceptual changes brought about by technological innovation. For example, the opposition between reality and virtuality, the physical and chemical consumption of film, and the zero consumption of digital photography. However, the ability to edit data and images is a major feature of digital technology, which has changed long-standing visual aesthetics and aesthetic tastes. Digital images are images that have been digitally processed by computer hardware and are usually expressed in a surreal way, which traditional images cannot achieve. The traditional cinema viewing situation is similar to art on shelves, and the author's subjective intention is conveyed to the audience through an efficient transmission system. Interactive imaging devices combine the aesthetic characteristics of both imaging and installation and are a product of the fusion of digital imaging and installation art, producing a unique aesthetic quality. As passive receivers, the audience can interpret the work in various ways through their own cognition. If traditional images are the art of "viewing" for people, then digital images are the art of "engaging" the audience. After combining digital images with installation art forms, the interaction and participation of the audience can generate meanings beyond those expressed by digital images themselves. This interpretation does not distort or alter the original intention of the work itself, and the relationship between the audience and the visual space is more like a one-way channel. Since traditional images always appear in relatively enclosed spaces and conditions, and are therefore presented to the audience, people often hold a revered attitude towards traditional images.

Key technology	*Function*
Neural network architecture	VGGNet, ResNet, etc., are used to extract the features of the image.
Content loss function	Measure the difference in content between the generated image and the input image.
Style loss function	Measure the difference in style between the generated image and the specified style.
Total variation loss function	Keep the texture smooth in the generated image.
Optimization algorithm	Gradient descent algorithm, Adam algorithm, etc., are used to solve the model parameters.

Table 1: Key technologies.

Table 1 shows the Key technologies. Countless holographic images are now scattered throughout museums, galleries, and art galleries. The arbitrary participation and departure of viewers increase the randomness of the space, transforming them from a fixed visual projection point to mobile visitors in the installation space. Through various forms of interaction and communication, transform a pure visual structure into a domain that reflects perception. The randomly flickering digital light and shadow in these large projection devices have replaced closed narrative structures and rigid frames. In terms of artistic structure, the main difference between interactive image installations and those that use perspective to create a sense of space lies in the construction of squares. Faced with a work that does not follow artistic conventions, the audience cannot establish a Gestalt or "frame" it. Therefore, only by experiencing "infinite presence" can it be understood and explored. Multimedia devices that require audience activation in order to be activated, their subjective consciousness of the audience is dispersed and does not play a cohesive role.

4 CONSTRUCTION AND APPLICATION OF STYLE TRANSFER MODEL

Image style transfer is an important image editing task that utilizes the texture and style of the style image to render the style of the content image. The image style transfer methods based on the global correlation matrix can be divided into image optimization-based and model optimization-based methods according to the different optimization objects. In recent years, the rapid development of image style transfer has benefited from the emergence of convolutional neural networks, which have been widely used in advertising design, art creation, film special effects rendering and other work tasks. Based on ensuring the semantic structure of content images, style images are well integrated into content images to create new works of art with distinctive styles, that is the process of re-creating existing works of art. The research on current image style transfer methods mainly focuses on two mainstream methods: image style transfer based on global correlation matrix and image style transfer based on generative adversarial networks. This method obtains feature information of style images through model training and achieves mapping from content images to stylized images. The image style transfer method based on generative adversarial networks achieves image-to-image conversion through dynamic learning to generate corresponding image distributions, but this method requires paired datasets. The image style transfer method based on generative adversarial networks achieves image-to-image conversion through dynamic learning to generate corresponding image distributions, but this method requires paired datasets. This method greatly improves the efficiency of image style transfer, and the generated stylized images do not have the problem of losing content image details. Figure 1 shows the CNN structure.

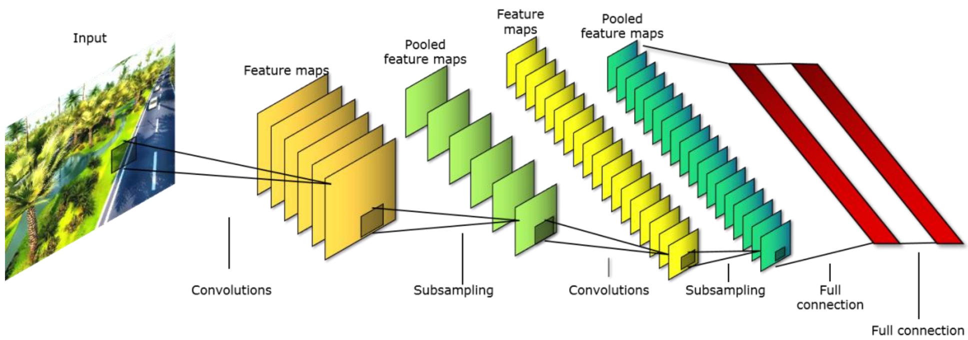

Figure 1: CNN structure.

This article analyzes the expression of image features in convolutional neural network layers at different depths. The study proposes a context encoding-based image style transfer method, which constructs an image conversion network and a loss network. To study the features extracted by different layers in convolutional neural networks, the features extracted by the corresponding convolutional layers were visualized using the backpropagation algorithm. By introducing a context encoding module and adding instance regularization after the convolutional layer, the network can converge more quickly. Finally, adjust the activation function of the output layer to improve the quality of the generated image. The semantic extractor serves as a feature loss and optimizes the generator by extracting high-level semantic information from the content image as a constraint. This method solves the semantic loss of stylized images and distortion of object edges in image style transfer. Thus, the convolutional layers required for extracting content and style features are determined, laying the foundation for the subsequent work in this article. This method is based on the framework of conditional generative adversarial networks and constructs a generator, discriminator, and semantic extractor. The generator and discriminator dynamically optimize the minimum and maximum values to learn low-level information such as the texture and colour of the style image. This allows the network to learn the image's translation invariance. This process is represented by expression (1), denoting the convolution kernel:

$$h_{ij}^{k} = \tanh\left(W^{k} * x_{ij}\right) + b_{k} \tag{1}$$

In this context, W^k signifies the weight, whereas b_k designates the offset.

Typically, a convolution layer incorporates numerous convolution kernels of identical dimensions. After applying each kernel to the input, a distinct feature map is generated. As a result, the convolution layer's comprehensive output emerges as a three-dimensional tensor. Activation functions bridge the gap between input and output signals, converting the former to generate the latter. Unlike a linear process, these functions activate neurons when the input exceeds a predetermined threshold. By integrating activation functions, convolutional networks gain an enhanced capacity for nonlinear representation:

$$f\left(x\right) = \frac{1}{1+\exp\left(-x\right)} \tag{2}$$

As the input passes through the activation function, its output is limited to a range of [0,1]. But, as the input nears the extremes of the function, the output stabilizes at 1 or 0, unaffected by the precise input value. This situation, labelled "gradient vanishing," causes the gradient to approach zero during backpropagation. Thus, the neuron's error can't be efficiently communicated, significantly affecting the training process.

Before integrating CAD data into the deep learning style transfer model, it's crucial to undertake preprocessing measures. This ensures data precision, uniformity, and the model's efficient utilization. Pretreatment mainly covers three key aspects: data cleaning, standardization, and feature extraction. These features may include the thickness, shape, colour, and texture of lines, as well as the spatial relationship and layout between design elements. Effective feature extraction can provide enough information for the style transfer model to understand and simulate different design styles. The aforementioned process can be expressed mathematically through the subsequent formula:

$$X_{preprocessed} = f_{preprocess}\left(X_{raw};\theta_{preprocess}\right) \tag{3}$$

Here, X_{raw} denotes the initial CAD information, $f_{preprocess}$ signifies the preprocessing function, $\theta_{preprocess}$ represents the preprocessing variable and $X_{preprocessed}$ stands for the data that has undergone preprocessing.

After undergoing preprocessing, the data will then proceed to the style transfer model for its training phase. The refinement of this model typically revolves around minimizing a designated loss function. The progression of this training is mathematically expressed by the subsequent formula:

$$\theta_{\mathrm{model}} = \arg\min_{\theta} L\left(Y, f_{\mathrm{model}}\left(X_{proprocessed};\theta\right)\right) \tag{4}$$

In this context, Y designates the intended output of the model, f_{model} represents the style transfer model itself, θ stands for the model's adjustable parameters, L denotes the loss function and θ_{model} signifies the optimal model parameters achieved through the training process.

Once the training is finalized, it's imperative to assess the model's interaction efficiency. This assessment can be conducted by contrasting the model-assisted interaction duration with the conventional interaction time. The evaluation metric can be mathematically formulated as:

$$E = \frac{T_{traditional} - T_{\mathrm{model}}}{T_{traditional}} \times 100\% \tag{5}$$

In this context, $T_{traditional}$ signifies the duration of traditional interaction, T_{model} represents the time taken for interaction aided by the style transfer model and E denotes the percentage improvement in efficiency achieved.

Develop a perception framework for the artistic style migration in new media, deriving the adequacy metric for this style migration as outlined below:

$$fitness\ \vec{x} = \begin{cases} f\ \vec{x} & If\ feeasible \\ 1 + rG\ \vec{x} & Otherwise \end{cases} \tag{6}$$

When considering the optimal design of new media art at the grey pixel level f, a computer vision resolution model is formulated utilizing the grey moment invariant feature decomposition approach.

$$\begin{aligned} W_u\ a,b\ &= e^{i2\pi k \ln a} \times \frac{K}{\sqrt{a}} \left\{ \left[\frac{ae^{\frac{j2\pi f\min}{a}\ b-b_a}}{f_{\min}} - \frac{e^{\frac{j2\pi f\max}{a}\ b-b_a}}{f_{\max}} \right] \right. \\ &\left. + j2\pi\ b-b_a \left[Ei\ j2\pi f_{\max}\ b-b_a\ - Ei\left(\frac{j2\pi f_{\min}}{a}\ b-b_a \right) \right] \right\} \end{aligned} \tag{7}$$

$$b_a = 1 - a \left(\frac{1}{af_{\max}} - \frac{T}{2} \right) \tag{8}$$

Within this context, $Ei\ \cdot$ signifies the output resulting from the recombination of visual information features in new media art, incorporating a model recognition approach to craft the desired new media artwork.

Applying the style transfer model to new media art design can achieve a variety of creative effects and artistic style innovation. The following are some specific application scenarios:

Artistic style innovation: Artists can use the style transfer model to transfer different artistic styles into their own works, thus creating a brand-new artistic style. For example, transferring the style of oil painting to photography can give the photos the same texture and colour as oil painting.

Personalized customization: Users can upload their own photos or select their favorite works of art as reference images and use the style transfer model to generate personalized works of art with specific styles. This personalized service has a broad application prospect in the new media art market.

Real-time interactive creation: Combined with CAD interactive technology, artists can adjust and control the parameters and effects of style transfer in real-time on the CAD platform, so as to create more flexibly and efficiently. This real-time interactive creative way can greatly improve the artist's creative experience.

By carefully designing and training the style transfer model and combining it with CAD interactive technology for real-time interactive creation, more unique and creative new media works of art can be realized.

5 RESULT ANALYSIS AND DISCUSSION

5.1 Experimental Environment

In this article, a variety of works of art and original images are selected to construct a data set, and the necessary pretreatment is carried out. In the aspect of model parameter configuration, the pre-training model based on CNN is adopted, the loss function is designed in combination with content loss and style loss, and the Adam optimization algorithm is used for training. The experimental environment is equipped with a high-performance GPU and the necessary deep-learning framework and library to ensure the efficiency of model training and reasoning. Table 2 shows the detailed experimental environment configuration, including the main models or versions of hardware and software.

Name	Model/version
Processor	Intel Xeon Gold 6248R
Graphics Processing Unit	NVIDIA Tesla V100 SXM2
Memory	512GB DDR4 ECC REG RAM
Storage	2TB NVMe SSD
Operating system	Ubuntu 18.04 LTS
Deep learning framework	TensorFlow 2.0
Programming language	Python 3.7
CUDA Version	CUDA 11.0
CuDNN version	cuDNN 8.0

Table 2: Experimental environment.

5.2 Experimental Results

In the experiment, a series of artistic images with different scales (including resolution and detail complexity) were selected as data sets. These images range from simple abstract paintings to complex realistic paintings, aiming at comprehensively evaluating the performance of the algorithm in different scenes. Figure 2 is an image after partial style migration.

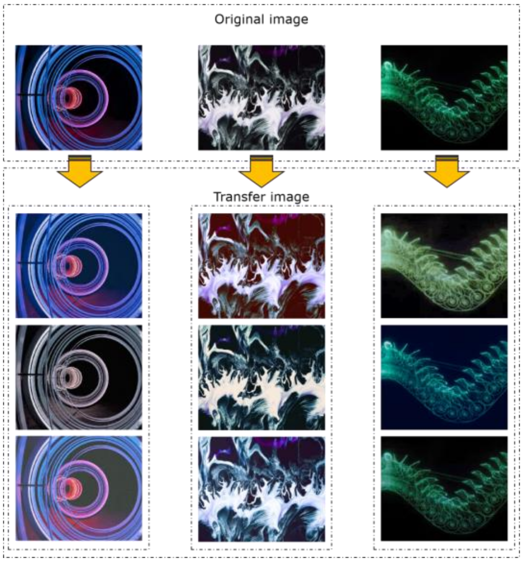

Figure 2: Style transfer image.

To prevent issues of over-fitting or under-fitting due to limited data samples and insufficient dataset diversity, we employ a data preprocessing approach akin to the aforementioned fine-grained datasets for data enhancement. Specifically, techniques like flipping, rotating, translating, and scaling are utilized to augment the artistic image dataset. Referring to Figure 3, for the flipping operation, each training image undergoes horizontal or vertical flipping with a 50% chance. This simulates images from various perspectives, enabling the model to grasp the style attributes of the image in multiple directions. For the rotation operation, rotate slightly around the centre of the image, and each image can be rotated counterclockwise by a certain angle (such as 10 degrees) to increase the robustness of the model to local subtle changes in the image. In translation, without changing the image boundary, each image is moved to the left or right by several pixels (such as 5 pixels) and moved up or down by fewer pixels (such as 3 pixels) to simulate the tiny movement of the image in the plane. For scaling operation, the image is reduced by a certain proportion (such as 90%) without changing the overall size of the image.

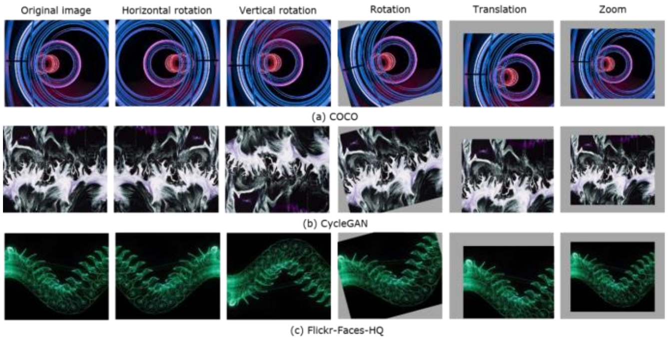

Figure 3: Data augmentation examples for training sets in three datasets.

This article explores the operational efficiency of style migration of artistic images of different scales under different node numbers. As shown in Figure 4, when the image scale is small, with the increase in the number of nodes, the time required for style migration does increase, but the growth rate is not significant. However, when the image scale gradually increases, the advantages of multi-nodes begin to appear, which can significantly improve the recognition efficiency and processing speed.

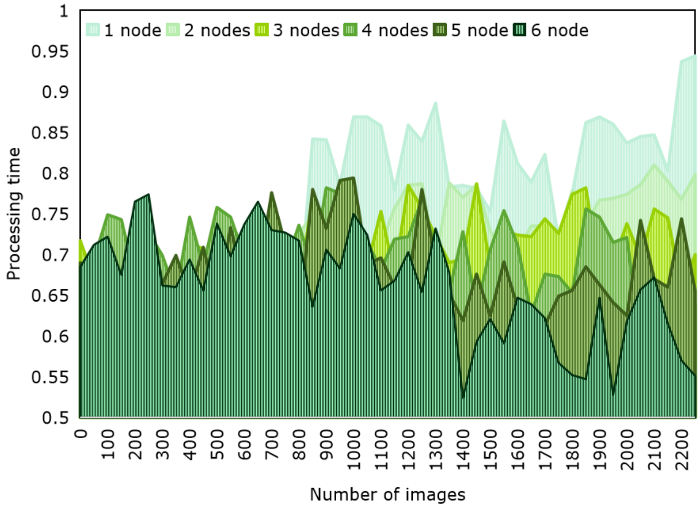

Figure 4: Image style migration consumes time.

When dealing with large-scale or high-complexity artistic images, multi-node parallel processing can effectively improve the efficiency of the algorithm and reduce users' waiting time.

Next, the time-consuming task of transferring the image style of new media art is compared with the method of Neural Style Transfer and the CycleGAN model. As shown in Figure 5, the CycleGAN method takes a long time to process artistic images, especially when processing large-scale images, and its performance bottleneck is more obvious. The Neural Style Transfer method can significantly improve the processing speed on the premise of ensuring the quality of style transfer.

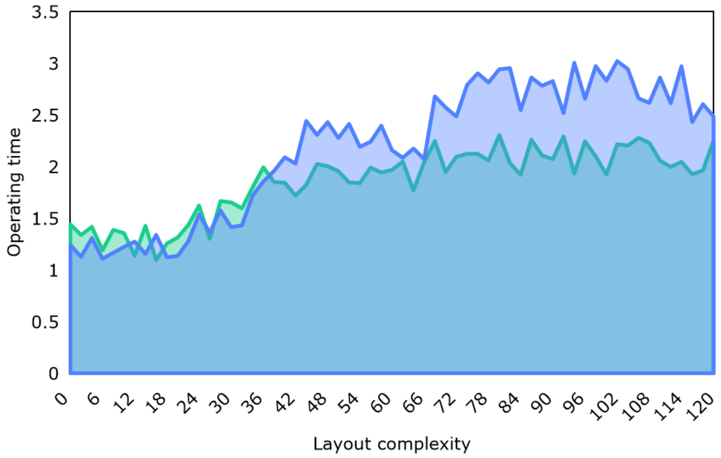

Figure 5: Time consumption test for image style transfer processing.

This comparative result verifies the advantages of the Neural Style Transfer method in dealing with the task of image style transfer of new media art, especially when dealing with large-scale images.

In order to further verify the performance of the Neural Style Transfer method, the error between the neural style transfer method and the CycleGAN algorithm in the image style transfer task is tested. As shown in Figure 6, the error of the Neural Style Transfer method is about 30% lower than that of CycleGAN. This result shows that the Neural Style Transfer method has higher stability when dealing with the task of artistic image style transfer.

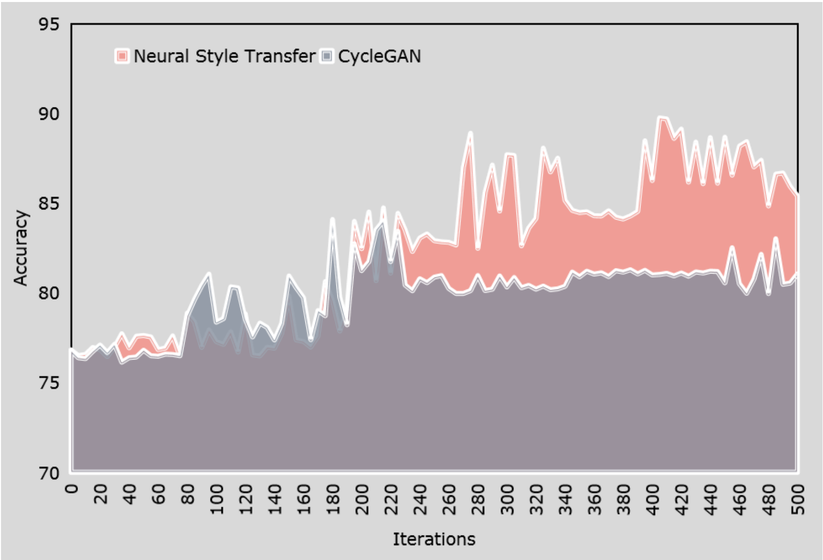

Figure 6: Error test of different algorithms.

In conclusion, we evaluate the F1 scores of various algorithms in artistic image style transfer tasks. Referring to Figure 7, our proposed algorithm outperforms traditional methods by over 10% in terms of F1 score for artwork image style transfer. This finding unequivocally demonstrates the superior performance of the Neural Style Transfer approach in handling artwork image style transfer tasks.

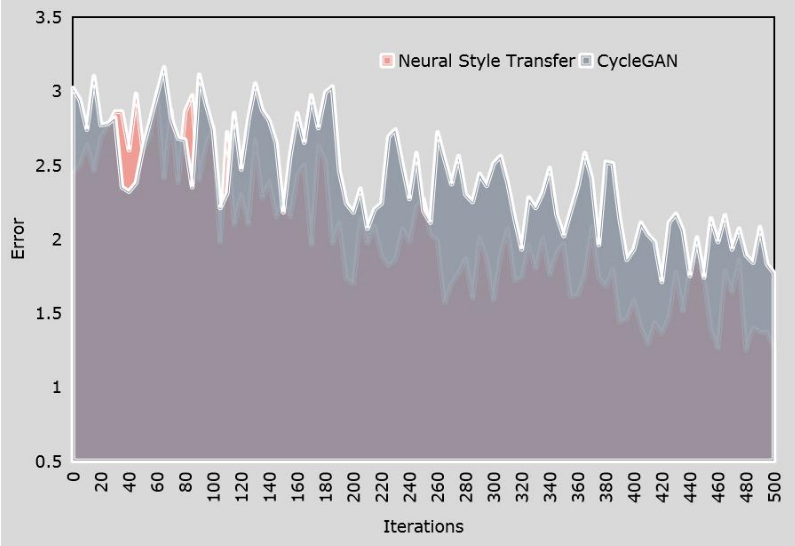

Figure 7: Comparison of recall of artistic image style migration.

5.3 Discussion

Image style transfer is an important field of computer vision and a current research hotspot and difficulty. This article proposes a deep learning-based image style transfer method for image style transfer tasks. In addition, in order to improve the semantic expression of stylized images for content images, this paper constructs paired datasets with different styles based on context encoding-based image style transfer methods. Used for training and testing image style transfer methods based on semantic adaptation. Starting from the fact that features extracted from convolutional layers of different depths have different characteristics, the shortcomings of current model-optimized image style transfer methods have been solved. The entire network consists of an image conversion network and a loss network, which adopt a structure of downsampling residual network upsampling in the image conversion network. We have improved its image conversion network by proposing a context encoding-based image style transfer method, which enhances the quality of the generated stylized images. After each convolutional layer in the image conversion network, instance normalization is used instead of the usual batch normalization. Multiple residual blocks are connecting the channels between downsampling and upsampling. Add a context encoding module between channels in the residual block, and add a context encoding module within the channel after the second upsampling. Compared with the CycleGAN method, neural style transfer excels in handling style transfer in new media art images. The experimental results demonstrate the effectiveness of the method proposed in this chapter in image style transfer tasks. Compared with similar methods, our method has improved network convergence speed and stylized image quality. Using conv4_2 in the VGG16 network as a semantic extractor to represent feature loss, the model structures of the generator, discriminator, and semantic extractor were constructed. Through experiments, it has been verified that compared with context encoding-based image style transfer methods, the generated stylized images have more semantic information in content images.

6 CONCLUSIONS

In the field of new media art, neural style transfer technology has shown unparalleled advantages. It can efficiently complete recognition and processing tasks in a short period, providing artists with a wider and more complex range of style conversion options. This method not only greatly improves the speed of image style conversion but also eliminates the need for artists and audiences to endure long waits. This outstanding performance makes neural style transfer technology a powerful assistant for artistic image style conversion. Compared with other technologies such as CycleGAN, neural style transfer performs better in style conversion of new media art images. Moreover, while maintaining the uniqueness of style transitions, it significantly reduces error rates, ensuring the accuracy and stability of artistic works. When faced with large or complex artistic images, the multi-node parallel processing ability of neural style transfer is particularly outstanding. Not only does it excel in accuracy, but it also performs excellently in stability, further consolidating its leading position in this field.

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REFERENCES

[1] Calilhanna, A.: Ogene Bunch music analyzed through the visualization and sonification of beat-class theory with ski-hill and cyclic graphs, The Journal of the Acoustical Society of America, 148(4), 2020, 2697. https://doi.org/10.1121/1.5147469

[2] Dai, Y.; Wu, Z.: Mobile-assisted pronunciation learning with feedback from peers and/or automatic speech recognition: A mixed-methods study, Computer Assisted Language Learning, 36(5-6), 2021, 861-884. https://doi.org/10.1080/09588221.2021.1952272

[3] Danchenko, N.: Acousmatic music: principles of graphic visualization, Bulletin of Kyiv National University of Culture and Arts Series in Musical Art, 3(1), 2020, 37-47. https://doi.org/10.31866/2616-7581.3.1.2020.204337

[4] Dong, Y.; Yang, X.; Zhao, X.: Bidirectional convolutional recurrent sparse network (BCRSN): an efficient model for music emotion recognition, IEEE Transactions on Multimedia, 21(12), 2019, 3150-3163. https://doi.org/10.1109/TMM.2019.2918739

[5] He, G.: Schema interaction visual teaching based on smart classroom environment in an art course, International Journal of Emerging Technologies in Learning (IJET), 15(17), 2020, 252. https://doi.org/10.3991/ijet.v15i17.16441

[6] Liu, M.; Huang, J.: Piano playing teaching system based on artificial intelligence–design and research, Journal of Intelligent & Fuzzy Systems, 40(2), 2021, 3525-3533. https://doi.org/10.3233/JIFS-189389

[7] Liu, S.; Li, T.: AVG comprehensive practice reform of digital media art based on fuzzy theory, Journal of Intelligent and Fuzzy Systems, 38(1), 2020, 1-10. https://doi.org/10.3233/JIFS-179592

[8] Maba, A.: Computer-aided music education and musical creativity, Journal of Human Sciences, 17(3), 2020, 822-830. https://doi.org/10.14687/jhs.v17i3.5908

[9] Ng, D.-T.; Ng, E.-H.; Chu, S.-K.: Engaging students in creative music making with musical instrument application in an online flipped classroom, Education and information Technologies, 27(1), 2022, 45-64. https://doi.org/10.1007/s10639-021-10568-2

[10] Peng, B.; Sirisuk, M.: Exploration of CAD and neural network integration in art design and cultural heritage protection, Computer-Aided Design, 21(18), 2024, 128-144. https://doi.org/10.14733/cadaps.2024.S18.128-144

[11] Pei, Z.; Wang, Y.: Analysis of computer aided teaching management system for music appreciation course based on network resources, Computer-Aided Design and Applications, 19(S1), 2021, 1-11. https://doi.org/10.14733/cadaps.2022.S1.1-11

[12] Pelliccia, L.; Bojko, M.; Prielipp, R.: Applicability of 3D-factory simulation software for computer-aided participatory design for industrial workplaces and processes, Procedia CIRP, 99(10), 2021, 122-126. https://doi.org/10.1016/j.procir.2021.03.019

[13] Zhang, B.; Rui, Z.: Application analysis of computer graphics and image-aided design in art design teaching, Computer-Aided Design and Applications, 18(S4), 2021, 13-24. https://doi.org/10.14733/cadaps.2021.S4.13-24
[14] Zhang, Y.; Yi, D.: A new music teaching mode based on computer automatic matching technology, International Journal of Emerging Technologies in Learning (IJET), 16(16), 2021, 117-130. https://doi.org/10.3991/IJET.V16I16.24895
[15] Zhu, W.: Study of creative thinking in digital media art design education, Creative Education, 11(2), 2020, 77-85. https://doi.org/10.4236/ce.2020.112006