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Computer-Aided Design AND APPLICATIONS

Artistic Style Transformation Based on Generative Confrontation Network

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Abstract. Due to the continuous growth of artificial intelligence (AI), artistic style transformation has become a highly concerned research field. It aims to apply one artistic style to another, generating works of art with new styles. At present, Generate Adversarial Networks (GAN) and Computer Aided Design (CAD) technologies have become two important methods in the study of artistic style transformation. This article aims to explore the application of GAN and CAD technology in the study of artistic style transformation. In the article, a series of different types of art works were selected, including painting, sculpture, and architecture, respectively, using GAN and CAD techniques for style conversion. Through the analysis and comparison of results, it was found that the Inception Score (IS) score of the GAN model was basically stable at over 90%, and the Structural Similarity Index (SSIM) between artistic images was around 0.957. Moreover, artists have a high rating for generating artistic works, and the images generated through style transformation using GAN models have been recognized and appreciated by artists in terms of visual effects, creativity, and artistic value. This further proves the effectiveness and superiority of the GAN model in artistic style transformation.

Keywords: Generate Adversarial Networks; Computer Aided Design; Transformation of artistic style
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1 INTRODUCTION

In the digital age, art has crossed national boundaries and races, and has become a global common spiritual wealth. The transformation of artistic style, that is, creating a unique way of integration between different artistic forms, has always been the dream pursued by artists. With the growth of digital technology and AI, more and more researchers began to try to use computer technology to realize artistic style transformation. Agnese et al. [1] conducted a comprehensive investigation provided an overview of their classification. Through research and analysis of relevant papers, we found that adversarial neural networks have significant advantages. Compared with traditional methods, adversarial neural networks can better learn the mapping relationship between text and images, generating more diverse and innovative images. In addition, adversarial neural networks can also achieve automatic image repair and optimization by training automatic encoders, further improving image quality. Among them, production countermeasure network and CAD technology are two important technical means. Fiber art is a traditional form of art. Carmen [2] explored how to combine information literacy with fiber art pattern design, injecting new vitality into fiber art through digital image technology. By obtaining and handling customer needs and feedback, designers can better understand their needs and expectations, thereby better designing and producing fiber artworks that meet the requirements. In addition, information literacy can also help designers better utilize various design software and tools to improve design efficiency and accuracy, and use computer-aided design software for design and production. Fiber art pattern design is an art form that requires high creativity and skill. Through the cultivation of information literacy, designers can better grasp the basic principles and skills of pattern design, while combining computer-aided design software for efficient design and production. GAN can be used to generate high-quality data without pre-modeling; And CAD technology can help designers to carry out digital design and manufacturing work, improve design efficiency and product quality.

Deldjoo et al. [3] conducted a comprehensive investigation into adversarial recommendation systems, from attack/defense strategies to generating adversarial networks. Machine learning algorithms are widely used in recommendation systems, but they have also become important targets for attackers. A common attack method is to target the training data of machine learning models by adding malicious samples or creating noise to interfere with the model's training process. Another attack method is to explore system vulnerabilities and use rating manipulation or malicious evaluations to affect recommendation results. Matrix decomposition algorithms play an important role in collaborative filtering recommendation systems. Attackers can disrupt the integrity of the matrix through malicious behavior or creating false evaluations, thereby affecting recommendation accuracy. In terms of defense strategies, matrix filling algorithms can be used to repair damaged matrices, or more robust collaborative filtering algorithms can be used to reduce dependence on matrix integrity. Therefore, they have great potential in the study of artistic style transformation.

Generative countermeasure network is a deep learning (DL) model, which learns a potential distribution through training data and generates new data samples. The use of computer-aided arts and crafts can reduce designers' manual operation time, improve design efficiency and accuracy. By using computer technology and software, designers can design more accurately, reduce errors and defects, and thus improve design quality. Computer assisted arts and crafts can provide designers with more creative space and possibilities, such as using virtual reality technology for design ideas and demonstrations, enabling designers to create more innovative and unique design works. By reducing manual operations and material waste, computer-aided arts and crafts can reduce production costs and resource waste. Computer assisted arts and crafts design works can be easily displayed and disseminated on computers, facilitating communication and cooperation between designers and clients or others. Deng and Chen [4] analyzed its current status and future development direction. Some researchers use AI technology to transfer the style of arts and crafts works, integrating different styles of works, and creating brand new designs. In addition, researchers have developed an AI based arts and crafts design assistance system that can automatically generate design plans based on user needs and historical design data, providing reference for designers. Its purpose is to generate high-quality and real images. In the transformation of artistic style, GAN can learn the distribution of an artistic style through training and generate new works of art. Fuentes et al. [5] During the training process, the generator attempts to generate false images that can deceive the discriminator, while the discriminator strives to distinguish between true and false images. This adversarial process helps to improve the quality of generated images. In addition, conditional parameters play a crucial role in cGANs, allowing the network to generate images under certain conditions. For example, in optical image translation tasks, these conditions may include source images, target categories, or other attributes. It should be noted that although cGANs perform well in many tasks, they may also have some issues, such as mode collapse and difficulty in training.

Therefore, selecting appropriate network structures and training strategies for specific tasks is very important. The generator will receive one or more conditional inputs, such as text descriptions or labels, and generate corresponding optical images. The discriminator will judge the generated optical image to determine its authenticity. Through this adversarial process, conditionally generated adversarial networks can learn the generation rules and distributions of optical images, thereby achieving translation from text to optical images.

For example, GAN can be used to transform the style of an oil painting into watercolor painting or sketch and other art forms. CAD technology is a general term for Computer Aided Design and manufacturing technology. It can help artists to create more effectively and provide more creative tools and means. Guo and Li [6] analyzed its advantages and challenges, and revealed its practical application through case analysis. In the field of film and television production, computer-aided design has become an indispensable part. Designers can use CAD software for scene modeling, character design, special effects production, and more. For example, in the movie "Avatar", director Cameron used CAD software to create a complete Pandora ecosystem, including various unique plants and animals. Through video streaming technology, directors and team members can view the scene effects in real-time during the shooting process, thereby better adjusting the shooting plan. In the transformation of artistic style, CAD can provide a more precise and accurate transformation method, and help artists to better realize the transformation of artistic style. Landscape painting, as a traditional art form, has unique charm and artistic value. He [7] provide reference for research in related fields. Deep learning to generate adversarial networks is an emerging in fields such as image processing and computer vision in recent years. This technology simulates data distribution by constructing generators and discriminators to generate new data. In terms of image processing, generating adversarial networks has shown strong potential in fields such as image generation and super-resolution reconstruction.

The main purpose of this study is to explore a new method of artistic style transformation, and analyze its effect through subjective evaluation of the generated results and comparison of objective indicators. In the transformation of artistic style, GAN can generate images that conform to a specific artistic style by training the generative confrontation network, and realize the free transformation between different artistic styles; CAD technology can help designers to do modeling, rendering and modification, and realize high-precision image processing and conversion. In this study, GAN and CAD technologies are applied to artistic style transformation. By analyzing and comparing the generated results, the advantages and disadvantages and application prospects of GAN and CAD technologies in artistic style transformation are discussed. Its innovations mainly include the following points:

(1) The method of transforming artistic style by using GAN model and CAD technology is proposed. Compared with the traditional artistic style conversion method, the use of GAN model can better capture the characteristics and styles of works of art and generate more realistic and diverse works of art.

(2) The subjective evaluation method is also combined to invite artists to grade the generated works of art, so as to assess the performance of the GAN model more comprehensively.

(3) The effectiveness and superiority of the GAN model in artistic style transformation are verified. In this article, many different types of works of art are verified superiority of GAN model in artistic style transformation, and it can generate high-quality works of art, which has been highly recognized and appreciated by artists.

Firstly, this article introduces the research background and significance of artistic style transformation, and the application of GAN and CAD technology in artistic style transformation. At the same time, it also expounds the purpose, method, result and conclusion of this article. Secondly, the principles, methods and application fields of GAN and CAD technology are introduced. Then, a method of artistic style transformation using GAN model and CAD technology is proposed. The design and implementation process of the experiment are described in detail. Finally, through the analysis of experimental verification and subjective evaluation results, the application prospect of GAN model in artistic creation and design is discussed, which provides new ideas and methods for artists, designers and researchers in related fields.

2 RELATED WORK

GANs is an architecture composed of two neural networks trained through competition to generate new samples. Jabbar et al. [8] will conduct an in-depth investigation into the generation of adversarial networks, exploring their variants, applications, and training methods, with the aim of providing valuable reference information for researchers and practitioners in related fields. Capture local features of the image through convolutional and pooling layers, and combine these features using fully connected layers to generate new images. RNN is a GAN variant suitable for sequence data. It captures the dependencies of sequence data through recurrent neural units and generates new sequence data using a generator and discriminator network. CAD can assist designers in architectural, interior, landscape and other design work. Through CAD software, designers can quickly and accurately create and modify design drafts, and perform precise measurements of dimensions and proportions. Using 3D modeling software, designers can create realistic 3D models and render them to simulate real-world lighting and material effects. This can help designers better preview the design effect and identify potential issues and defects. These technologies can create immersive virtual environments, allowing designers and clients to experience and observe design effects in greater depth. Through VR and AR technology, designers can identify potential problems in the early stages of design and make timely adjustments, thereby improving design quality and efficiency. Jin and Yang [9] believes that computer-aided design software can help students establish three-dimensional models and render and adjust their details. This allows students to have a more intuitive understanding of the finished product during the design phase and better grasp the overall effect of the design. Through computer-aided design software, students can try various innovative design ideas. For example, using virtual reality technology for design conception and demonstration, or utilizing computer-generated design data for innovative design and optimization. This can help students evaluate and optimize the design scheme during the design process, improving the practicality and feasibility of the design. By operating computer-aided design software, students can intuitively experience the combination and composition of design elements, deepening their understanding of concepts such as space, form, and color. To use computer-aided design software to solve practical design problems and improve teaching quality and effectiveness through demonstrations and case studies.

Liu and Yang [10] explores the contemporary art computer-aided design teaching model centered on innovation, providing reference for cultivating artistic talents with innovative practical abilities. In the field of contemporary art, computer-aided design teaching not only teaches students basic design skills, but also focuses on cultivating students' innovative thinking and ability. Through innovative teaching, students' creativity can be stimulated, their design level can be improved, and new vitality can be injected into the development of contemporary art. In the field of contemporary art, computer-aided design teaching not only teaches students basic design skills, but also focuses on cultivating students' innovative thinking and ability. Through innovative teaching, students' creativity can be stimulated, their design level can be improved, and new vitality can be injected into the development of contemporary art. Artistic image is the result of an artist's reflection and construction on real life. This reflection and construction not only reflects the artist's understanding and cognition of reality, but also reflects their keen insight into multiple factors such as society and culture. Maltseva [11] explored artistic images as a result of reflection and construction of reality, analyzed how they reflect reality, society, and culture, and based on this, explored their promotion and summary. Artistic images convey the artist's reflection on reality through images. This kind of reflection can be critical or constructive. For example, in the history of modern Western art, surrealist artists reflect on human alienation in modern society by creating images that transcend the real world. They combine illogical elements in reality and reveal the absurdity behind their appearance. This way of image reflection provides people with a new perspective to examine the real world. With the development of technology, building material design has entered the digital era. Generative adversarial networks (GAN), as a deep learning technology, provide new solutions for the design of complex building materials. Mao et al. [12] explored how to use generative adversarial networks to design complex building materials, and analyzed their advantages and application prospects. The generator generates new data by learning data distribution, while the discriminator determines whether the generated data is true. In building material design, generating adversarial networks can be used to optimize the performance, structure, and appearance of materials.

In practical applications, semantic segmentation models often face performance degradation due to differences in data distribution and challenges in domain adaptability. To address this issue, Tasar et al. [13] In semantic segmentation, the goal is to assign each pixel in the image to a specific category. Color mapping is a technique that maps the color information of each pixel to a specific category, thereby achieving semantic segmentation of images. The generator attempts to generate fake images that can deceive the discriminator, while the discriminator strives to distinguish between the real image and the generated fake image. Adversarial networks are a method of simulating data distribution and generating realistic images or data by constructing generator and discriminator networks. Wang et al. [14] analyzed generative adversarial networks in computer vision. Unsupervised generative adversarial networks are generative adversarial networks that do not require supervised learning. It learns the true distribution of data by constructing an autoencoder and generates new data. Semi supervised generative adversarial networks combine the advantages of unsupervised learning and supervised learning, and can be trained using partially annotated data as well as unlabeled data. Supervised generation of adversarial networks is the most commonly used type, which trains through annotated data and generates new data similar to real data. Convolutional neural network generation adversarial network is a type of generative adversarial network that uses convolutional neural networks. It is mainly used for processing image data, which can learn the underlying features of the image and generate new images. Differential generative adversarial network search zero sample learning (D-GAN-ZS) has been proposed, which can train and generate without annotated data and has broad application prospects. Yan et al. [15] improve training efficiency and generation quality by using differentiable generators and discriminators. Zero sample learning refers to using existing unlabeled data for training and classification without labeled data. In D-GAN-ZS, the generator uses random noise as input and generates images similar to the target category. The discriminator judges the real image and the generated image, and updates the network parameters through backpropagation. Due to the lack of annotated data, D-GAN-ZS is trained using unsupervised learning to optimize by maximizing the judgment error of the discriminator.

Yu and Luo [16] proposed a clothing pattern generation method based on multi-scale self attention improvement to generate adversarial networks, aiming to improve the diversity and innovation of pattern design. A review of relevant research was conducted, followed by research questions and hypotheses, followed by an introduction to research methods and experimental design. This mechanism allows the model to capture the features of patterns at different scales, thereby gaining a more comprehensive understanding of the complexity and details of the patterns. Through multi-scale analysis, the model can better capture the hierarchical structure and detailed information of patterns, thereby generating richer and more realistic patterns. Medical image segmentation is one of the important tasks in medical image processing, aiming to classify and label different regions in the image. However, due to the complexity and uncertainty of medical images, achieving accurate medical image segmentation is a challenging task. Among them, the unsupervised domain adaptive content consistency generation adversarial network (UDA-CCGAN) has shown good performance and application prospects in medical image segmentation. Zhang et al. [17] detailed the application and advantages of UDA-CCGAN. Unsupervised domain adaptive methods have been proposed to solve cross domain problems in medical image segmentation. Zou [18] with the aim of providing reference for research and practice in related fields. Dynamic visual recognition technology refers to the use of computer image processing technology to recognize and track targets in dynamic scenes by analyzing and understanding videos or image sequences. Dynamic visual recognition technology refers to the use of computer image processing technology to recognize and track targets in dynamic scenes by analyzing and understanding videos or image sequences.

Based on the above research, this article applies GAN and CAD technology to artistic style conversion, aiming at exploring a new artistic style conversion method, and analyzing its effect through subjective evaluation of the generated results and comparison of objective indicators. This study can not only provide artists with new creative methods, but also provide useful reference for research in computer graphics, image processing and other fields.

3 PRINCIPLES AND METHODS OF GAN AND CAD TECHNOLOGY

GAN and CAD are two widely used technologies in image processing and computer vision. Among them, GAN is a kind of generative countermeasure network, and its principle is based on the generative model of DL, and the distribution of data is learned by training neural networks, thus generating new numbers similar to the training data. The advantage of GAN is that it does not need to model in advance, but learns directly from the data distribution through sampling, so it can generate very real data. In addition, GAN can also be used for image classification, object detection, image restoration and other tasks, and the generated image quality is very high. CAD technology is a computer-aided technology widely used in machinery, architecture, electronics and other industries. It can help designers to do modeling, rendering and animation design, and improve design efficiency and quality. The basic principle of CAD technology is to use computer graphics technology and three-dimensional modeling technology to transform designers' creativity into digital three-dimensional models. In the application of CAD technology, designers can model, modify and render through computer graphic interface. At the same time, CAD technology can also be combined with computer-aided manufacturing technology to transform the designer's design into the actual manufacturing process and production process. The use of this digital design and manufacturing technology can greatly improve production efficiency and product quality.

4 APPLICATION OF GAN AND CAD TECHNOLOGY IN ARTISTIC STYLE TRANSFORMATION

The transformation of artistic style is a process of applying one artistic style to another. In the transformation of artistic style, GAN can generate images that conform to a specific artistic style by training the generative confrontation network. Through this antagonistic training, the generator and discriminator will constantly optimize their network parameters until the generator can generate an image with a high degree of similarity to the target artistic style. In application, GAN can realize the transformation between different artistic styles through transfer learning technology. Specifically, any image can be transformed into an image that conforms to a specific artistic style by using the existing pre-training model. This conversion method can greatly improve the conversion efficiency and image quality, and can realize the free conversion between different artistic styles.

CAD technology can help designers with modeling, rendering and animation design. In artistic style transformation, CAD technology can be used to extract the features and styles of images, and these features and styles should be applied to other images. Designers can use CAD technology to model, render and modify images, so as to get images that meet specific artistic styles. The application of CAD technology in artistic style conversion can realize high-precision image processing and conversion. Designers can adjust and modify the details of images through CAD technology, so as to realize more accurate artistic style conversion. At the same time, CAD technology can also be combined with GAN and other technologies to further improve the efficiency and effect of artistic style conversion.

5 ARTISTIC STYLE TRANSFORMATION BASED ON GENERATIVE CONFRONTATION NETWORK AND CAD

5.1 Training and Optimization Process of GAN Model

The training and optimization process of GAN model is a complex and delicate process. It is needed to select appropriate data sets, initialize network parameters, train discriminators and generators, optimize models and assess models. In the training process, it is needed to adjust the training parameters and optimize the parameters of the algorithm according to the actual situation to improve the quality and stability of the model. This article first prepares a data set, which contains real data and generated data. Real data is a sample from a dataset, while generated data is a sample generated by a generator. In this article, before training the GAN model, these data are preprocessed, such as normalization and noise removal.

Before the training begins, the network parameters of generator and discriminator need to be initialized. These parameters include the weight and bias of the neural network. In this article, random initialization method and pre-trained model are used to initialize these parameters. The generator formula of GAN model is:

$$g, h_t^M = M\left(f_t, h_{t-1}^M; \theta_m\right) \tag{1}$$

$$O_t, h_t^W = W\left(x_t, h_{t-1}^w; \theta_W\right) \tag{2}$$

The discriminator formula is:

$$f = F\left(x; \varnothing_r\right) \tag{3}$$

$$D_{\varnothing}(s) = sigmoid\left(\varnothing_1, F\left(s; \varnothing_r\right)\right) = sigmoid\left(\varnothing_1, f\right) \tag{4}$$

$$\sum_{j=1}^{n} T_{ij} = \frac{1}{m} \tag{5}$$

$$\sum_{i=1}^{m} T_{ij} = \frac{1}{n} \tag{6}$$

Before training the discriminator, a noise sample is a fake picture. Then, the fake picture and the real picture are input into the discriminator, so that it can better judge the authenticity of the input picture. Before training the generator, a noise sample is used as input, and then a new picture is generated by using the generator. The new picture and the real picture are input into the discriminator, and the network parameters of the generator are updated by the back propagation algorithm. Figure 1 shows the GAN model architecture.

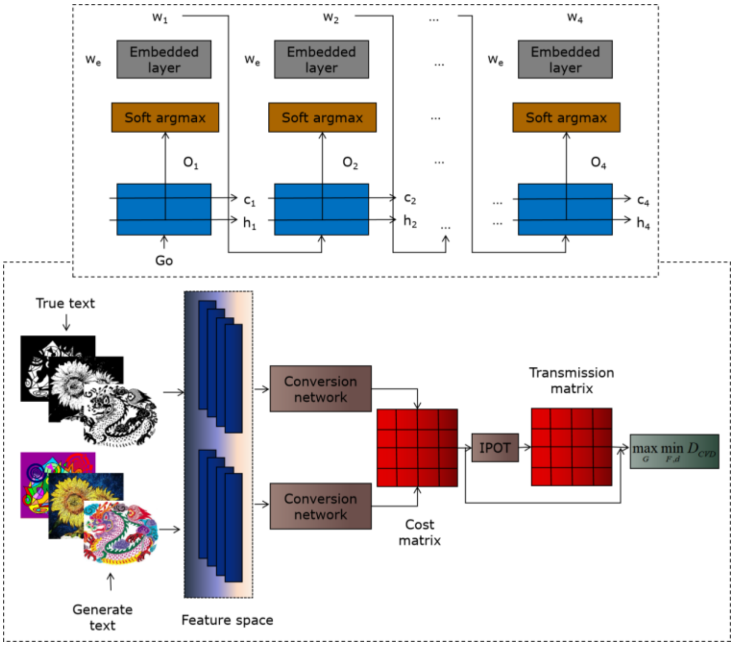

Figure 1: GAN model architecture.

This process function is expressed as the following formula:

$$\min_{G} \max_{D}(D,G) = E_{x\sim p_{data}(x)}[(\log D(x))] + E_{z\sim p_{g}(z)}[(\log(1-D(G(z))))] \tag{7}$$

In the training stage, it is needed to constantly adjust the parameters of the generator, so that it can better generate pictures that conform to the data set distribution. In this article, during the training process, the parameters of GAN model are continuously optimized to improve the quality and stability of the model.

After the training, it is needed to assess the GAN model to understand the generation effect and quality of the model. Some evaluation indicators can be used. In this article, IS and Frechet Inception Distance (FID) are used. IS and FID are both indicators for evaluating the image quality generated by raw GAN. These two evaluation indicators can measure the quality and diversity of the generated pictures. In addition, this article selects some objective indicators, such as PSNR and SSIM, to compare and analyze the generated works of art.

5.2 The Realization Process of Artistic Style Transformation

The realization process of artistic style conversion mainly involves three steps: image preprocessing, training of content encoder and style encoder, and training of generator and discriminator.

(1) Image preprocessing: Image preprocessing is the first step in the process of artistic style transformation. Because the input image may have problems such as inconsistent size, different brightness and noise interference, it is needed to preprocess the image to extract the features and contents of the image. In the stage of artistic style conversion, the input image needs to be preprocessed first to improve the quality and stability of the image, so as to better carry out the subsequent style conversion. Image preprocessing mainly includes the following steps: image cropping: cutting the input image into images of the same size for subsequent processing. Grayscale: Convert a color image into a grayscale image to reduce the processing complexity and calculation. Normalization: Normalize the pixel values of images to the same proportion, so as to avoid the influence of differences between different images on subsequent processing. Denoising: filter the image to remove noise and interference in the image. Feature extraction: Using image processing techniques, such as edge detection and corner detection, the features and contents in the image are extracted. Through the above steps, the input image can be converted into a standardized image, and the features and contents can be extracted, which provides a basis for the subsequent style conversion.

(2) Training of content encoder and style encoder: In the application of artistic style conversion, the content encoder can convert the input artistic image into the target content artistic image, while the style encoder can convert the target content artistic image into the target style artistic image. In the training process, the BP algorithm can be used to update the parameters of GAN, so as to gradually optimize the quality and fidelity of the generated artistic images. The network structural unit of the encoder is Gated Recurrent Unit (GRU). Let the status of the current GRU unit be:

$$h_t = [h_t^1; h_t^2] \tag{8}$$

Among them, $[h_t^1; h_t^2]$ means to connect two hidden state vectors. If h_t^1, h_t^2 is both $d_1 \times d_2$, then the connection is $d_1 \times 2d_2$ dimension. The input of the decoder is the coded z and the target image s_z, then the hidden state h_t of each neuron has an abstract representation:

$$h_t = GRU(h_{t-1} w_t, z, s_z) \tag{9}$$

The true and false images are input into the corresponding discriminators according to the domain of the real image and the target domain input when the generated image is constructed. The final overall loss function is:

$$L_{total} \arg\min_{G} \max_{D} \sum_{i,j\in\{A,B,C,D\}} L_{adv}(G, D_i) + \lambda_{cyc} L_{cyc}(G) \tag{10}$$

Among them, λ_{cyc} controls the parameter ratio of anti-loss and reconstruction loss in the generator, and the best generation effect can be obtained by adjusting the ratio. In the experiment, set $\lambda_{cyc} = 8$.

(3) Training of generator and discriminator: Generator and discriminator are two key neural network models used to realize artistic style transformation. The generator converts the input image into a new image that conforms to the target artistic style. In the training process, we need to use the output of content encoder and style encoder as input, and use generator and discriminator to generate new images. The training stage of the generator can be divided into the following steps: converting the input image into the target content image through the content encoder; Converting a target content image into a target style image through a style encoder; During this process, both the generator and discriminator will use the BP (Back Propagation) algorithm for training. The goal of the generator is to deceive the discriminator, making it unable to distinguish between the generated image and the real image, while the discriminator's goal is to identify the generated image as accurately as possible. Through backpropagation and optimization algorithms, both the generator and discriminator will gradually improve their performance to achieve this goal.

During the training process, the generator will receive the target style image as input and generate a new image. The discriminator compares the generated new image with the real image and calculates the differences between them. This difference will be used to adjust the network parameters of the generator and discriminator to optimize the quality and fidelity of the generated images. This process will be repeated until the generator and discriminator reach a certain level of performance. Through the above three steps, the process of artistic style transformation can be realized. Figure 2 shows the original artistic style image, and Figure 3 shows the optimized artistic style image.

Figure 2: Original artistic style images.

Figure 3: Optimized artistic style image.

It can be seen from the figure that by training the content encoder, style encoder, generator and discriminator, we can learn the mapping relationship from the input image to the target artistic style, and generate high-quality artistic style transfer images.

6 SIMULATION RESEARCH AND RESULT ANALYSIS

This section first collects works of different artistic styles, including oil painting, watercolor painting, sketch, etc., as training and testing data sets. Secondly, the data is preprocessed. Generally speaking, the collected data often contains some noise and irrelevant information, which needs to be cleaned. Data cleaning mainly includes operations such as processing missing values, smoothing noise values, identifying and processing abnormal values. Through data cleaning, the quality and reliability of data can be improved, which provides a better foundation for subsequent experiments and analysis. When collecting data from multiple data sources, it is needed to integrate and store the data from multiple data sources. Data transformation includes normalization, discretization and feature extraction, which makes the data more standardized and easier to process. For large-scale data sets, data specification is needed to reduce the dimension and complexity of data. Data specification includes clustering and principal component analysis, which makes the data more compact and easier to handle. Then, the GAN model is used to train the data and learn the distribution and characteristics of different artistic styles. Finally, the trained GAN model is used to transform the style and generate new works of art. Let's do the experiment.

IS is an evaluation method based on the Inception model. The authenticity score and the diversity score. Diversity score measures the diversity of generated images in different categories. Finally, IS obtains a comprehensive score by exponentially averaging the authenticity score and diversity score of the generated image. A higher IS indicates that the generated images are good in authenticity and diversity. Figure 4 shows the IS score of GAN model.

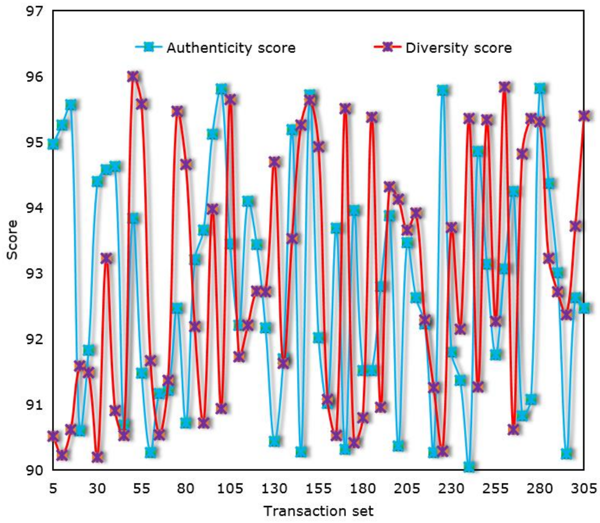

Figure 4: IS score of GAN model.

The IS score of the GAN model is basically stable above 90%. This means that the images generated by using GAN model have high authenticity and diversity. Specifically, the high IS score of the GAN model indicates that both the authenticity score and the diversity score of the generated image are excellent.

FID is also an index to assess the image quality generated by GAN, which is based on the features extracted by the Inception model. Frechet distance measures the similarity between two data sets, and the smaller the value, the more similar the two data sets are. The advantage of FID is that it considers the diversity of images and the similarity of distribution, and can more accurately assess the quality of images generated by GAN. Figure 5 shows the FID situation of GAN model.

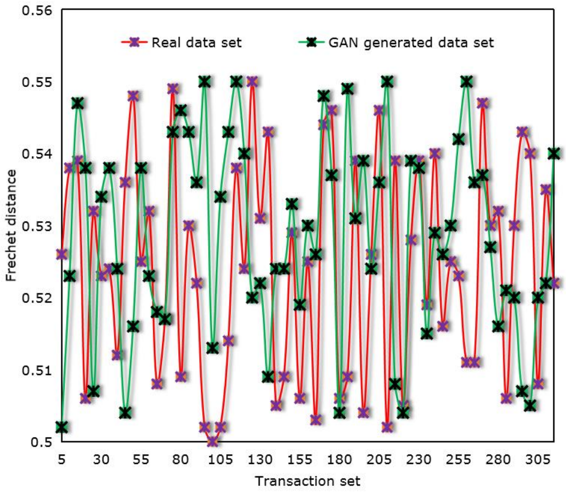

Figure 5: FID of GAN model.

As can be seen from Figure 5, the Frechet distance between the real data set and the data set generated by GAN is short. It shows that the model can learn and simulate the distribution and characteristics of real data well and generate more realistic images.

In addition, this article selects some objective indicators, such as PSNR and SSIM, to compare and analyze the generated works of art. Mean square error (MSE) is obtained by performing difference operation on two images and squaring them. The larger the PSNR value, the higher the quality of the reconstructed image. SSIM is used to measure the similarity between two images. It assesses the similarity of two images, and the larger the value, the more similar the two images are. Figure 6 shows the PSNR of artistic images generated by the proposed GAN model. Figure 7 shows the SSIM situation between artistic images.

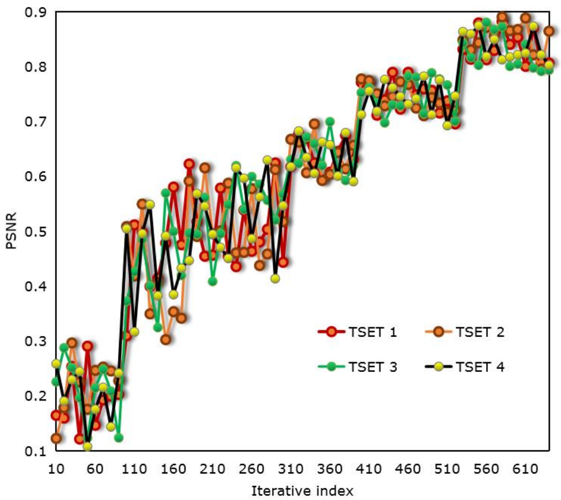

Figure 6: PSNR situation.

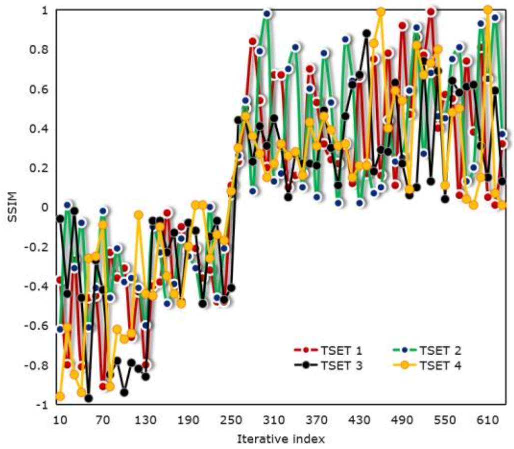

Figure 7: SSIM situation.

Although a high PSNR value indicates a high reconstruction quality of the image, it does not necessarily mean that the generated image is visually satisfactory. Sometimes, a high PSNR value may only mean that the generated image is similar to the target image at the pixel level, but it does not guarantee that the generated image has a good visual effect or artistic sense overall. Therefore, when evaluating images generated by GAN, in addition to the PSNR value, other factors such as visual effects, artistry, creativity, etc. need to be considered. They are visually close. On the whole, the proposed GAN model has good performance in generating artistic images. This further proves the validity and reliability of the model.

Subjective evaluation is a direct and intuitive evaluation method, which can reflect the subjective feelings and aesthetic judgments of human beings on the generated images. As professional artists, artists are highly professional in their sensitivity and aesthetic standards of works of art. Therefore, the artist's rating of generated works of art can be used as one of the important reference indexes to assess the performance of GAN model. In this section, after using the trained GAN model to transform styles and generate new works of art, artists are invited to make subjective evaluation on the generated works of art to assess their quality and diversity. The specific artist rating is shown in Figure 8.

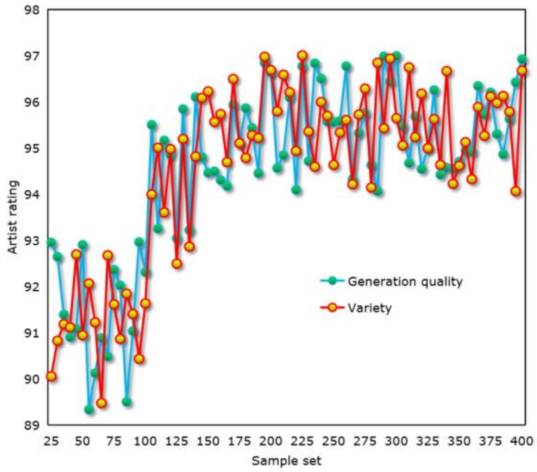

Figure 8: Artist rating.

As can be seen from Figure 8, the artist has a high score on the generated works of art, which shows that the image generated by style conversion using GAN model has been recognized and appreciated by the artist in terms of visual effect, creativity and artistic value. This further proves the effectiveness and superiority of GAN model in artistic style transformation.

In this section, experiments are carried out on data sets of different artistic styles such as oil painting, watercolor painting and sketch, and training and learning are carried out by using GAN model, thus realizing the transformation between different artistic styles. Through the subjective evaluation of the results and the comparison of objective indicators, it is found that the GAN model can better learn and simulate the distribution and characteristics of different artistic styles and generate new works of art.. At the same time, CAD technology can provide artists with more precise and accurate conversion methods and help them better realize the conversion of artistic style.

7 CONCLUSIONS

Through experiments and analysis, this article discusses the use of GAN and CAD in the study of artistic style transformation. In this article, a method of artistic style transformation using GAN model and CAD technology is proposed. Compared with the traditional artistic style conversion method, the use of GAN model can better capture the characteristics and styles of works of art and generate more realistic and diverse works of art. And the performance of the model is excellent and reliable. Generally speaking, GAN and CAD technology have great advantages in the quality and diversity of artistic style transformation, especially in dealing with complex artistic style transformation. In addition, in the experiment, the new works of art generated by style conversion using GAN model have been highly recognized and appreciated by artists in subjective evaluation. This further proves the effectiveness and superiority of GAN model in artistic style transformation, and also shows the potential and value of this model in practical application.

It is also found that the performance of GAN technology is influenced by many factors, such as training data set, network structure and optimization algorithm. In order to further improve the performance of GAN in artistic style transformation, future research can try to explore new network structure, optimization algorithm and training method. In addition, by combining other neural network technologies, the application scope of GAN in artistic style transformation can be further expanded. In a word, both GAN and CAD technologies have broad application prospects in artistic style transformation. It is believed that with the continuous growth of technology in the future, the application of GAN and CAD in artistic style transformation will be more and more extensive.

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