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Cultural Inheritance and Innovation Path of Digital Art: Integration and Development of Computer-Assisted Art Creation and Digital Media Technology

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ABSTRACT
Under the impetus of computer technology, the creation of digital art continues to develop, and computer-assisted creation has gradually become the mainstream of artistic creation. This paper is oriented to digital art innovation, in-depth exploration of computer-assisted art creation and its integration with the development of digital media. Through the in-depth analysis of computer-assisted art creation, this paper constructs an improved CycleGAN art pattern generation model by introducing the self-attention mechanism in the CycleGAN model on the basis of pattern generation. In the generation experiments of the improved CycleGAN model, the SSIM and PSMR values of the improved model in this paper are 0.721 and 17.563, and in the number of in-parameters, the model size, and the running speed are reduced compared with the traditional model, and the overall performance of the improved model is excellent. At the same time, the works based on the computer-aided art creation method of this paper compared with the traditional art creation works of the comprehensive average score increased by 11.40 points, further illustrating the more advantageous in computer-aided art creation. The study concludes by analyzing the path of the combination of computer-aided and digital media, and proposes a path for the integration and development of the two from multiple perspectives, which provides directions and ideas for the research on the integration and development of computer-aided and digital media technologies.

Keywords: computer-aided, attention mechanism, improved CycleGAN, pattern generation, art creation

1. Introduction

In the era of digitalization, social development and technological progress have had a great impact on people's lives. At the same time, digitization also puts forward new challenges and opportunities for cultural inheritance and innovation. The rise of digital technology enables people to communicate and

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exchange culture globally through the Internet [1-4]. As a result, traditional culture has a wider dissemination platform, for example, Chinese traditional music, painting and opera art have been appreciated and inherited by a wider international audience [5-7]. Digital art communication has played an important role in promoting the innovation and development of traditional culture and art. Digital technology has brought new ways of expression and creation methods for traditional art. For example, with the help of virtual reality technology, audiences can enjoy traditional opera performances immersively [8-11]. Through digital production and distribution, traditional music can be organically integrated with modern music. This digitalization innovation makes traditional arts more vital and creative [12-14].

However, digital distribution also brings some challenges to traditional culture and art. The development of digital technology has made the dissemination of information more rapid and extensive, but it has also caused information overload and fragmentation. The audience's focus and interest are scattered, and traditional culture and arts are difficult to gain lasting attention and recognition. In addition, digital communication has also brought new challenges to the copyright protection of culture and art [15-18].

This study is mainly oriented to computer-assisted exploration of computer-assisted art creation methods, and analyze its integration with digital media technology development path. This paper firstly analyzes the development of computer-aided art creation, and puts forward the idea of computer-aided art creation and the realization method. Then for the computer-aided technology, an improved CycleGAN art pattern generation model is constructed, and then its performance is verified through experiments. On this basis, the computer-aided art creation in this paper is compared with traditional art creation to further study the actual effect of computer-aided art creation. Finally, the relationship between computer-assisted and digital media is combined to discuss in depth the influence of digital media on computer-assisted art creation, and provide a strategy for the integration and development of computer-assisted art creation and digital media.

2. Computer-assisted digital art creation based on the development of the

2.1. Computer-assisted digital art based creation

2.1.1. Computer-assisted art creation based approach. Generative design is a design methodology that focuses on the design process and design guidelines. The concept of process-generative design refers to designing a program and then generating a design through that "program". In a certain sense, it is seen as a new and innovative way to abolish the role of the designer, return the authority of design to the public, and brainstorm. It provides a more democratic way of working in the design process. And nowadays, with the continuous development of digital information technology in the field of art creation, computers, together with the inclusion of designers and participants, constitute the main medium of digitally generated design. Based on the nature of the computer is a kind of logic and thinking way to think about the problem, while the essence of art creation is to find the problem and treat the problem description and personal emotion expression. Computer language is not only a tool for design, but also a way of artistic expression, the combination of art design and computer science and technology expands too many possibilities of artistic expression, in the art and cultural heritage, it allows artists to create art and emotional expression in a broader latitude, and then use the design and computer-assisted combination of to solve the problems that human beings can not solve, so as to create more forms of artistic art works and even scientific inventions.

2.1.2. The relationship between computer-assisted art creation and digital media. In traditional art creation, in terms of the medium of art creation, there is a strong limitation for the creative expression of the artist. In the heritage of art and culture, with the development of digital technology, digital media as the new media has become the mainstream media, which plays a vital role in the field of art using computer-aided creation, and at the same time, makes art creation become a form of interdisciplinary and cross-field cooperation. There has always been a very large distance between computers and real space, but this distance is rapidly shrinking in the field of new media art. For new media artists, especially interactive artists, all the concepts about the creation of art, the functioning of the world, and how to build a system are affected by computer technology. With the addition of digital media, art creation can make every participant a possible information audience and dissemination node, increasing the effectiveness of cultural transmission. Therefore, the function of creation is different from the traditional way of art creation, which is only in the hands of the artist, but more in the hands of the participants involved in the interactive behavior.

For the process of art creation, what the artist needs to do is not to re-interpret the information and express the ideas, but to re-organize the logic, formulate the rules of interaction, and grant the participants a tool for self-explanation. In the age of digital media, art creation is less and less concerned with the external characteristics of design, but more and more concerned with defining and forming some design methods, in order to generate, organize and output the results, furthermore, is to form a system to rely on, which relies on the formation of the system without the assistance of computer technology, which is precisely the reason for the rise of computer technology in the field of art.

2.2. Computer-assisted realization in artistic creation and cultural inheritance

2.2.1. Computer-generated technologies. Computer in the art creation and cultural heritage in the auxiliary mainly rely on computer programming language to realize, computer automatic generation of art design pattern is the most common in the field of art creation of computer aided way. Computer automatically generated patterns, mainly relying on computer programming language using algorithms to generate. In the field of art design, programming form is the design method, computer language and software is the carrier, and then generate different works of art effect. By organizing and summarizing the technical principles of computer algorithms in the automatic generation of patterns, including the mathematical formulas, algorithms for the deductive derivation of computer graphics. The development of programming art software visualizes programming, providing a programming language more suitable for art designers and a visual programming interface to generate dynamic pattern effects. Automatically generated by artificial intelligence, the pattern is generated directly through the software or website interface, which further reduces the creator's algorithmic knowledge reserves and the use of barriers, but also makes up for the creator's lack of basic drawing art skills.

Taking Chaotica fractal art software as an example, Chaotica fractal art software is based on the IFS iterative function system formed by python drawing algorithm. This kind of fractal software designs the basic algorithms into art software and provides users with a simple and easy-to-learn control interface.The design and generation method of Chaotica fractal art software is shown in Figure 1. According to the different needs of users and consumers, the whole process can be divided into two stages, stage one is suitable for small-scale industries, the generated patterns can be directly applied to the product, and stage two is suitable for designers with unique design needs to assist in the creation of design. The generated fractal pattern can be used as a separate pattern in fashion products, and can also be used for secondary design, forming new pattern combinations through the collage of bipartite and quadripartite patterns to realize the effect of full-printed patterns.

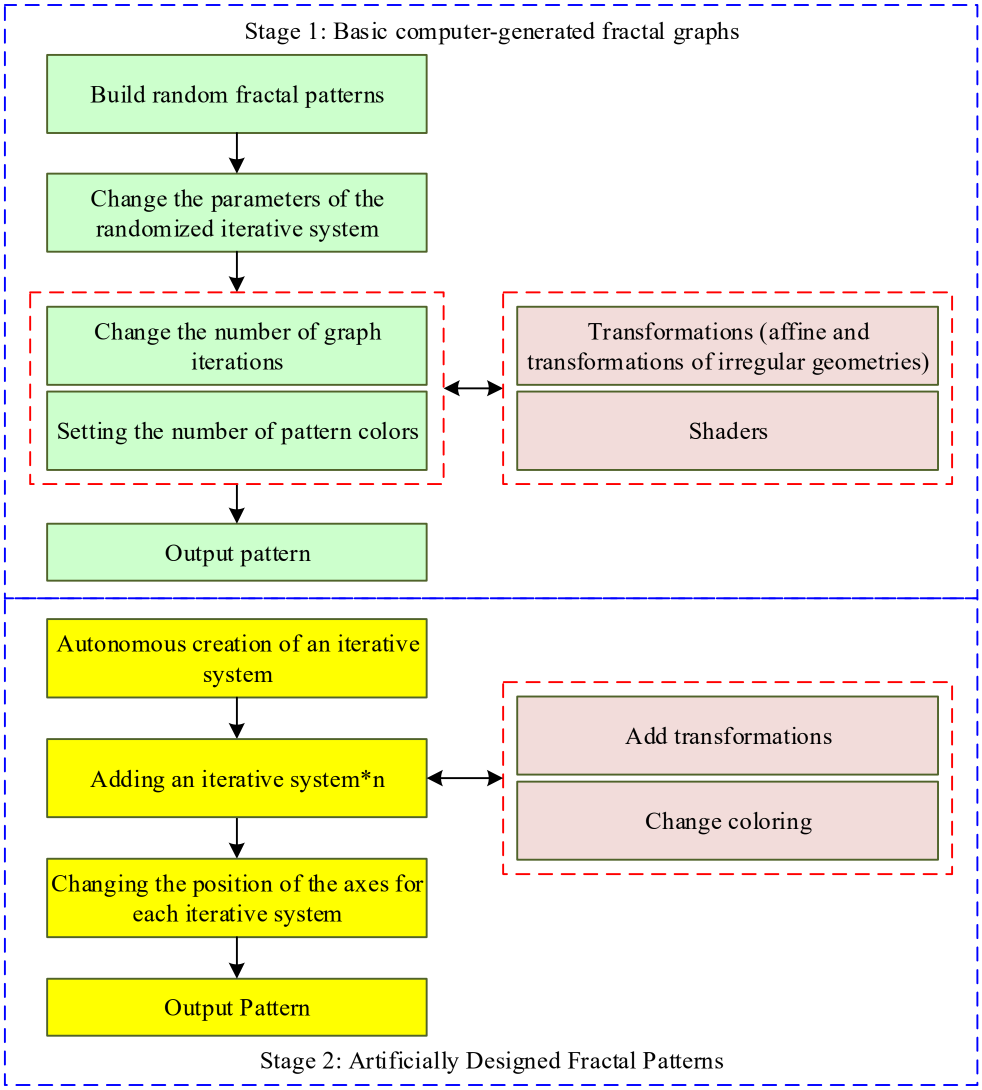

Fig. 1. The design generation method of Chaotica fractal art software

2.2.2. Computer-assisted Art Creation and Inheritance Based Ideas. Computer-assisted art creation provides more possibilities for art works, and at the same time, it also provides an effective means for cultural inheritance. Computer technology, by assisting artistic creation, allows creators to devote more time and energy to express the connotation and culture of the work in depth, which has a certain role in promoting cultural inheritance.

Based on the computer-assisted art creation ideas shown in Figure 2, computer-assisted and art creation is a mutual influence and interaction, therefore, the elements of art creation should closely follow the theme of the creation of the natural environment, the social environment, the subject of the expression of the spiritual elements, and around the core level to start a series of design behavior, so that the entire visual identity system between the elements of a more harmonious composition A whole, the main idea will be conveyed powerfully and effectively. The first step in the computer-aided art creation process is to determine the theme of the art design and find the pattern elements related to the theme. Under the computer-assisted, digital pattern elements are different from traditional pattern elements, with distinctive features of digital technology and a wide selection space, which requires the designer to filter all the elements obtained after the wild ideas, and determine the pattern elements that are most suitable for the expression of the theme. In the second step, according to the generation technology, determine the primary and secondary levels of elemental logical relationships, clarify the core elements and deal with the subordinate relationship. The logical relationship of the elements is divided into the mathematical logic of the algorithmic formula, the execution logic of visualization programming, the composition logic of fractal art, the algorithmic logic of artificial intelligence and so on. In the process of digital pattern creation, rational logical thinking and artistic aesthetics should be combined to make the generated pattern with digital aesthetic characteristics. In the third step, the secondary design of the generated pattern is carried out to ensure the harmony and unity of the visual system elements, so that the design elements are presented in an orderly manner. As the computer-generated patterns still have certain limitations in aesthetics and application, designers need to reintegrate and redesign the pattern components and formal characteristics based on the clothing structure to achieve the beauty of the pattern's proportions, rhythms and forms.

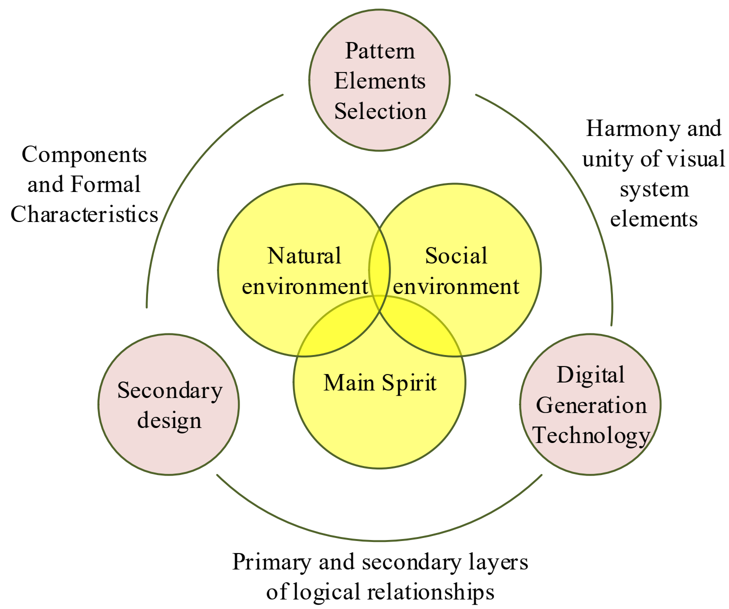

Fig. 2. A computer aided artistic thinking

3. Art pattern generation model based on improved CycleGAN

3.1. Artistic Pattern Generation Technology Analysis

3.1.1. Image style migration. The style migration technique is mainly realized by deep learning models, of which the most popular method is based on convolutional neural networks. The style migration loss function consists of two parts, content loss and style loss, which are used to preserve the content features of the original image and migrate the style features of the reference image, respectively. Content loss is used to ensure that the generated image retains the content features of the original image. It is quantified by calculating the difference between the generated image and the original image. The content loss function is:

$$L_{content}(C,G)=\frac{1}{2}\sum_{i,j}\left(C_{ij}-G_{ij}\right)^2 \tag{1}$$

Where, C_{ij} denotes the content features of the original image and G_{ij} denotes the content features of the generated image. The goal of content loss is to minimize the difference between C and G so that the generated image is similar to the original image in terms of content. Style loss is used to ensure that the generated image has the style characteristics of the reference image. The style loss is quantified by comparing the difference between the features of the generated image and the reference image. The style loss function is in the form of Gram matrix which is used to capture the correlation between the features and the style loss function is:

$$L_{style}(S,G)=\sum_{l=0}^{L}\frac{1}{4N_l^2M_l^2}\sum_{i,j}\left(G_{ij}^{(l)}-S_{ij}^{(l)}\right)^2 \tag{2}$$

The goal of style loss is to minimize the difference between C and G so that the generated image is stylistically similar to the reference image. By optimizing both the content loss and style loss components, the style migration algorithm is able to generate a new image with the content of the original image and the style of the reference image.

3.1.2. Adversarial Generative Networks. Adversarial Generative Network (GAN) is a deep learning model that generates data such as images, sounds and text.GAN consists of two different neural networks, a generator and a discriminator. The generator is responsible for generating samples, while the discriminator is responsible for recognizing whether a sample is real or generated. These two networks are trained through competitive learning, where the generator tries to generate more realistic samples, while the discriminator tries to distinguish between real and generated samples. In this process, the adversarial relationship between the generator and the discriminator motivates the generator to continuously improve its ability to generate samples. Eventually, the generator is able to generate samples that are indistinguishable from real samples. This mechanism makes GAN achieve remarkable results in the fields of sample data generation, image generation, image restoration, image conversion, text generation, etc. The GAN generative adversarial network model mainly realizes the parameterization of neural networks. The input is a random vector and the output can be regarded as a sample.

The loss function of the adversarial network consists of generator loss G and discriminator loss D. The generator loss function is:

$$\min_G V(G,D)=\mathrm{E}_{z\sim p_z(z)}[\log(1-D(G(z)))] \tag{3}$$

The generator tries to generate realistic data to deceive the discriminator. Its loss function is the discriminator's misjudgment of the data generated by the generator. The goal of the generator is to minimize the probability that the discriminator will not accurately recognize the generated data, i.e., the goal of generator G is to maximize $D(G(z))$, i.e., minimize $1-D(G(z))$.

The loss function of the discriminator is:

$$\begin{aligned}\min_D V(G,D)=\mathrm{E}_{x-p_{data}(x)}&[\log D(x)]\\ +\mathrm{E}_{z-p_z(z)}&[\log(1-D(G(z)))]\end{aligned} \tag{4}$$

The discriminator attempts to distinguish between real data and data generated by the generator. The goal of the discriminator is to maximize the probability that it correctly identifies the real data and the generated data, i.e., maximize $\log D(x)+\log(1-D(G(z))$.

3.1.3. Recurrent Generative Adversarial Networks. Cycle Generative Adversarial Networks (CycleGAN) is a powerful computer algorithm that enables seamless image transformations between different visual styles and domains.The advantage of CycleGAN is that it performs image style transformations without the need for pairwise data. Compared with the traditional image conversion method Pix2Pix, the latter needs to find the correspondence between the source image and the target style image to realize the style migration. However, in many application scenarios, it is very difficult to obtain image pairs with precise correspondences. CycleGAN breaks through this limitation by introducing the concept of cyclic consistency, which converts between two kinds of images without the need of correspondences. This feature greatly enhances the application scope and flexibility of the model, providing an effective and innovative solution for cross-domain image conversion.The CycleGAN network structure is shown in Fig. 3, which consists of two generators and two discriminators. During the training process, the generators and the discriminators will continuously engage in adversarial games to optimize their respective model parameters.

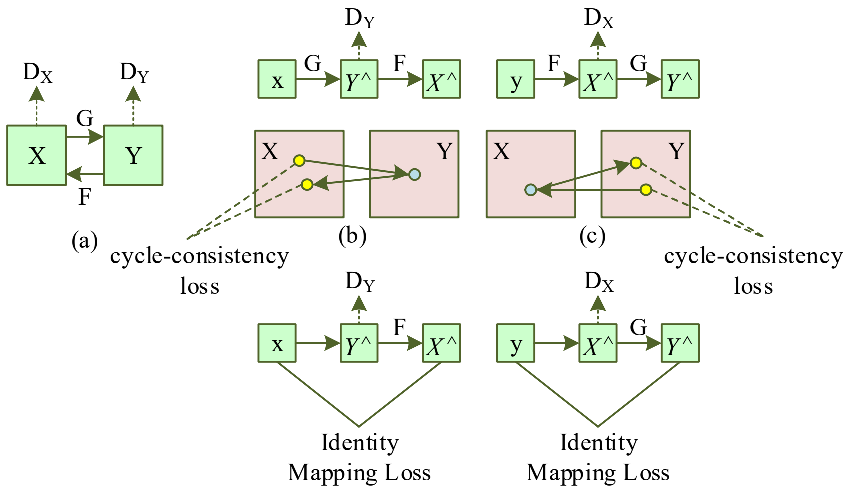

Fig. 3. CycleGAN network structure

The CycleGAN model loss function is mainly composed of the adversarial loss and the cyclic consistency loss. For generator G and discriminator D_Y over domain Y, the adversarial loss function is:

$$\begin{aligned} \mathrm{L}_{GAN}\left(G, D_y, X, Y\right) &= \mathrm{E}_{y \sim p_{data}(y)}\left[\log D_y(y)\right] \\ &+ \mathrm{E}_{x \sim p_{data}(x)}\left[\log\left(1 - D_y(G(x))\right)\right] \end{aligned} \tag{5}$$

For generator F and and discriminator D_x over domain X, the adversarial loss function is:

$$\begin{aligned} \mathrm{L}_{GAN}\left(F, D_X, Y, X\right) &= \mathrm{E}_{x \sim p_{data}(x)}\left[\log D_X(x)\right] \\ &+ \mathrm{E}_{y \sim p_{data}(y)}\left[\log\left(1 - D_X(F(y))\right)\right] \end{aligned} \tag{6}$$

where D_Y and D_X are discriminator networks that discriminate between Y and X. Generator G tries to convert the image of domain X to the image of domain Y, while generator F does the opposite. $\mathrm{E}_{x \sim p_{data}(x)}$ and $\mathrm{E}_{y \sim p_{data}(y)}$ represent the mathematical expectation of the samples in domain X and domain Y, respectively. $\log D_X(x)$ and $\log D_Y(y)$ represent the logarithmic value of the probability of a real image being recognized as a real image in the discriminator, respectively. $\log\left(1 - D_Y(G(x))\right)$ and $\log\left(1 - D_X(F(y))\right)$ represent the logarithmic value of the probability that the discriminator recognizes the image as false for the generated image.

The cyclic consistency loss function is:

$$\mathrm{L}_{cyc}(G, F) = \mathrm{E}_{x \sim p_{data}(x)}\left[\left\|F(G(x)) - x\right\|_1\right] + \mathrm{E}_{y \sim p_{data}(y)}\left[\left\|G(F(y)) - y\right\|_1\right] \tag{7}$$

Where, $\left\|F(G(x)) - x\right\|_1$ and $\left\|G(F(y)) - y\right\|_1$ denote the L1 paradigm. This loss function penalizes the model by calculating the difference between the original image and the image that has been cyclically transformed, making the transformation reversible and encouraging the generated image to maintain the information of the original image.The total loss function of the CycleGAN model is:

$$\begin{aligned} \mathrm{L}_{GAN}\left(G, F, D_X, D_Y\right) &= \mathrm{L}_{GAN}\left(G, D_Y, X, Y\right) \\ &+ \mathrm{L}_{GAN}\left(F, D_X, Y, X\right) + \lambda \mathrm{L}_{cyc}(G, F) \end{aligned} \tag{8}$$

3.2. Pattern Migration Algorithm Based on Improved CycleGAN Modeling

In the original CycleGAN model style migration task, the feature extraction mainly focuses on local features and neglects to capture the long-range dependencies in the image, which will lead to the limitation of the coherence and detail performance of the image content during the image transformation process. This will affect the learning efficiency of the model and the quality of the generated images. On the other hand, when the sample image scale is reduced or the image quality is poor, the details of the generated image will be lost.

For this reason, in this paper, the original CycleGAN model structure is improved for the problems of blurring, distortion, and missing details in the generated images, and the image enhancement preprocessing operation is performed on the training samples. The improved CycleGAN model training structure is shown in Fig. 4.The self-attention mechanism is a mechanism that can dynamically learn the relationship between features, which can help the network to better focus on the important parts of the image and improve the quality of the image transformation. By introducing the self-attention mechanism in the CycleGAN model, the generated image can better preserve the features and details of the image and reduce the appearance of artifacts and distortion. Meanwhile, in order to effectively suppress the loss of texture details during the style migration process, the VGG16 structure is added to the CycleGAN model to reduce the changes from the input image to the output image at the feature level, to improve the quality and accuracy of the image conversion, and to make the generated image clearer and more realistic.

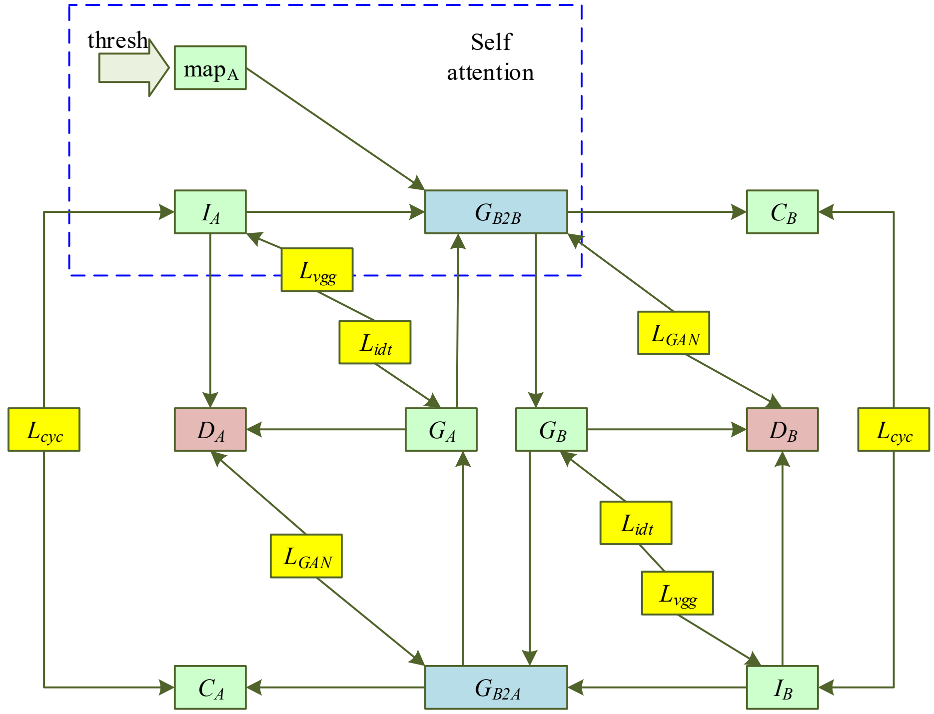

Fig. 4. Improve the structure of the CycleGAN model

4. Research on Art Pattern Generation Based on Improved CycleGAN

4.1. Experiments on Art Pattern Generation with Improved CycleGAN

4.1.1. Comparison of loss function results. In order to validate the art image generation effect of the improved CycleGAN model studied in this paper, pre-training is performed on the publicly available dataset monet2photo dataset, and the appropriate hyperparameters and training strategies are continuously adjusted.

Through the adversarial loss function, the training process between the generator and the discriminator reflects the competition and mutual enhancement between them. This competition and mutual enhancement process reflects the degree of convergence of the model as well as the quality of the generated images. As the training proceeds, the balance between the two is gradually realized, ultimately producing high-quality generated images.

In this paper, the original GAN, WGAN (Wasserstein GAN) and the improved CycleGAN in this paper are used for comparison respectively, and the loss changes are shown in Fig. 5. After training the loss function analysis, it can be seen that compared with the original GAN loss and WGAN loss, the improved CycleGAN loss used in this paper can achieve a lower drop when reaching the Nash equilibrium. The overall loss value changes between 0.65 and 1.80, and this phenomenon shows that the image generated by the generative network has improved quality and enhanced expressiveness, solves the problem of pattern collapse and gradient disappearance, and outperforms the other two methods in terms of results.

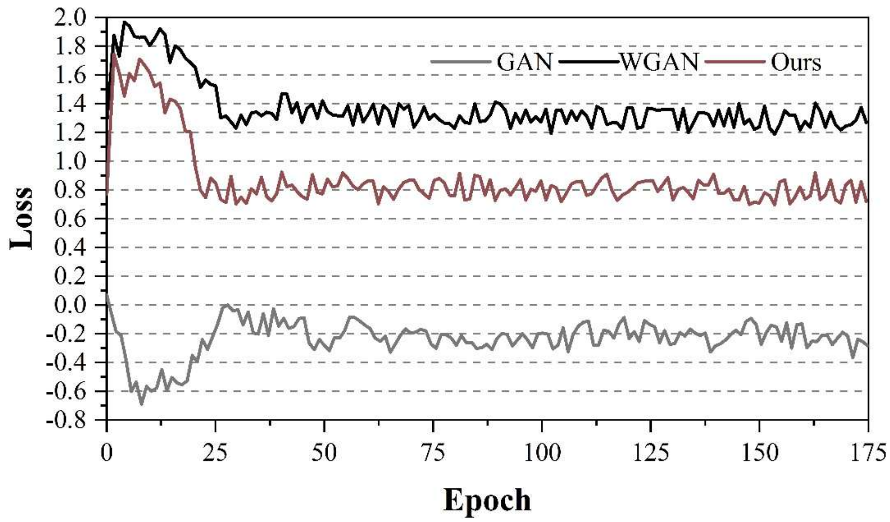

Fig. 5. Loss variation

4.1.2. Comparison of different network architectures. Compare the network architecture in this paper with the U-net network architecture, which is also a classical convolutional neural network structure and widely used in CycleGAN model. It is unique in having a U-shaped network structure and jump connections to retain more low-level feature information, which helps the generator to reconstruct the image more accurately. Through experiments, only different generator network architectures are used to compare the suitability of the U-net structure and the structure used in this paper for generating species for art creation by ensuring that the configuration parameters, loss functions, weights, and datasets are all the same. The comparison results of the network structure are shown in Fig. 6, and it can be seen that the Loss curve of this paper's network architecture converges faster, and starts to converge in 100 iterations, which is significantly better than the U-net network structure.

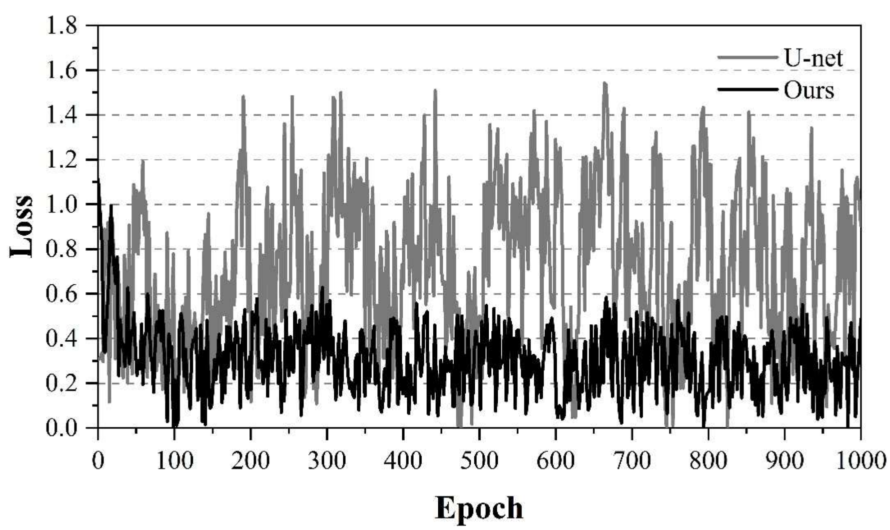

Fig. 6. Contrast results of network structure

4.1.3. Comparative experiments with different models. To further validate the generation effect of the improved model in this paper, the performance of GAN, WGAN, traditional CycleGAN and the improved CycleGAN model in this paper are compared in terms of generation quality and diversity. In order to measure the quality of evaluating the generated art patterns, two metrics, SSIM and PSNR, are used. The results of the comparison of the generation quality of different models are shown in Fig. 7.

The SSIM and PSMR values of the improved CycleGAN model in this paper are 0.721 and 17.563, respectively.By comparing with other models, it is clear that the improved CycleGAN model in this paper also performs better in terms of detail and quality.

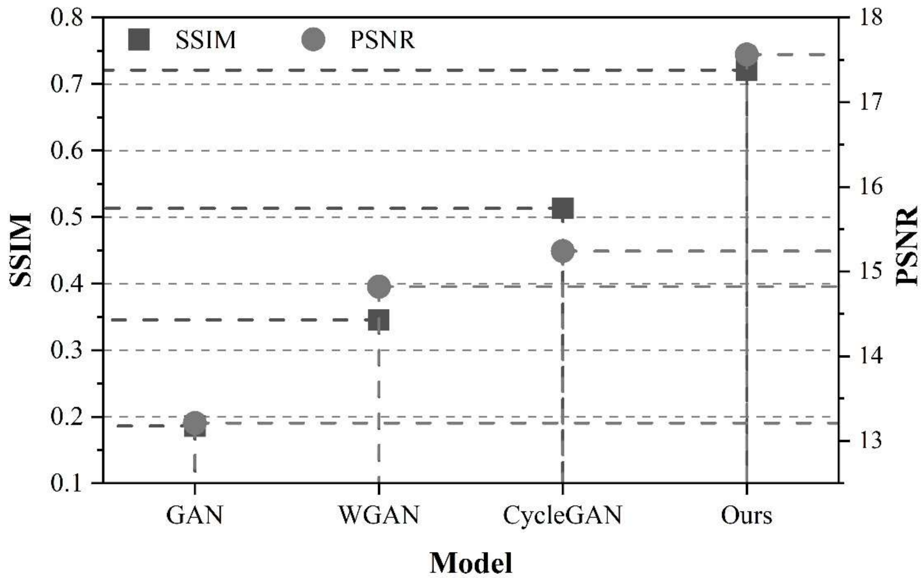

Fig. 7. Different models generate quality comparison results

To further ensure the effectiveness of the improved CycleGAN model, in this paper, the quality of image generation is kept unchanged on the basis of network lightweighting. The number of parameters, running speed and model size are used as evaluation metrics to evaluate the results, and the overall performance comparison of the model is shown in Table 1. In this paper, the number of parameters, model size, and running speed are reduced in the improved CycleGAN model compared to the traditional CycleGAN model, which are reduced by 4.176M, 15.57MB, and 0.59s, respectively.SSIM and PSNR are improved, and the improved CycleGAN model performs the best compared to the other models in each of the evaluation metrics.

Table 1. The integrity of the model can be compared

Generation model	Parameter quantity/M	Model size/MB	Running speed/s	SSIM	PSNR
GAN	10.175	37.85	0.086	0.186	13.211
WGAN	12.536	46.32	0.762	0.3456	14.821
CycleGAN	11.385	43.52	0.638	0.5132	15.241
Ours	7.209	27.95	0.048	0.721	17.563

4.2. Empirical study of artistic pattern generation

In this paper, the similarity between the generated image and the art pattern is calculated to evaluate the actual effect of the art out pattern generation generated by the previous experiments. The similarity index includes structure similarity, texture similarity and color similarity. The closer the similarity value is to 0, the less similar the generated target is to the art pattern, and the worse the effect is. The closer the similarity value is to 1, the more similar the target and the pattern are, and the better the effect is. In this paper, 8 patterns of art creation elements (denoted as A1~A8) are selected and the model of this paper is applied for pattern generation, and the similarity results of art pattern generation are shown in Table 2. As can be seen from the table, the average of structural similarity is the lowest (0.511), and the average of color similarity is the highest (0.857), which indicates that the art patterns generated by this paper's model are slightly lower in structural similarity, but still remain above 0.5. The overall average similarity is 0.721, and overall, the art patterns generated by the method in this paper have certain practicality and value in applying to art creation, and the generation effect is better.

Table 2. Similar results generated by artistic patterns

Numbering	Structural similarity	Texture similarity	Color similarity	Mean
A1	0.3956	0.7213	0.7892	0.635
A2	0.5415	0.6852	0.8955	0.707
A3	0.5269	0.6852	0.8242	0.679
A4	0.5532	0.9852	0.8631	0.800
A5	0.6687	0.8752	0.8950	0.813
A6	0.4856	0.7153	0.9120	0.704
A7	0.5942	0.8321	0.8932	0.773
A8	0.3215	0.8720	0.7853	0.660
Mean	0.511	0.796	0.857	0.721

5. Comparison of computer-based assisted art creation

Computer technology provides an effective creation tool for art creation, and this paper provides art creators with a pattern generation model with better performance based on the improved CycleGAN model. Next, based on the model assistance in this paper, 6 art creators are invited to perform actual creation comparison, while 10 experts are invited to rate the art creation (out of 100). Three creators will create artworks under the computer-assisted method of this paper, and the artworks will be labeled as JF1~JF3. Three other creators will create artworks in the traditional way, and the artworks will be labeled as CT1~CT3, with the same themes, materials and elements.

The scores of computer-assisted art creation are shown in Fig. 8, from which it can be seen that the three works created under the computer-assisted creation in this paper were given high evaluations by 10 experts, and the scores of the three works were all above 70 points. The average scores of works JF1, JF2 and JF3 are 84.9, 84.8 and 84.2, and the overall effect of the art creation based on the computer-aided in this paper is excellent.

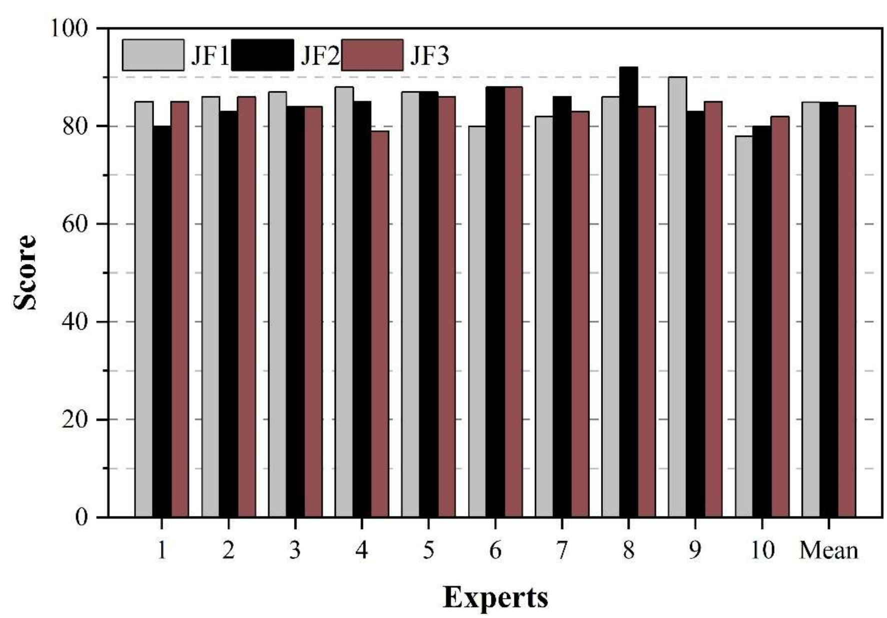

Fig. 8. Computer-aided artistic scoring

The scores based on traditional art creation are shown in Fig. 9.The scores of art creation works in traditional art creation mode are between 60 and 85, and the average scores of works CT1, CT2 and CT3 are 74.4, 72.8 and 72.5.The scores of works based on traditional art creation mode are relatively low compared to the scores of computer-assisted art creation in this paper.

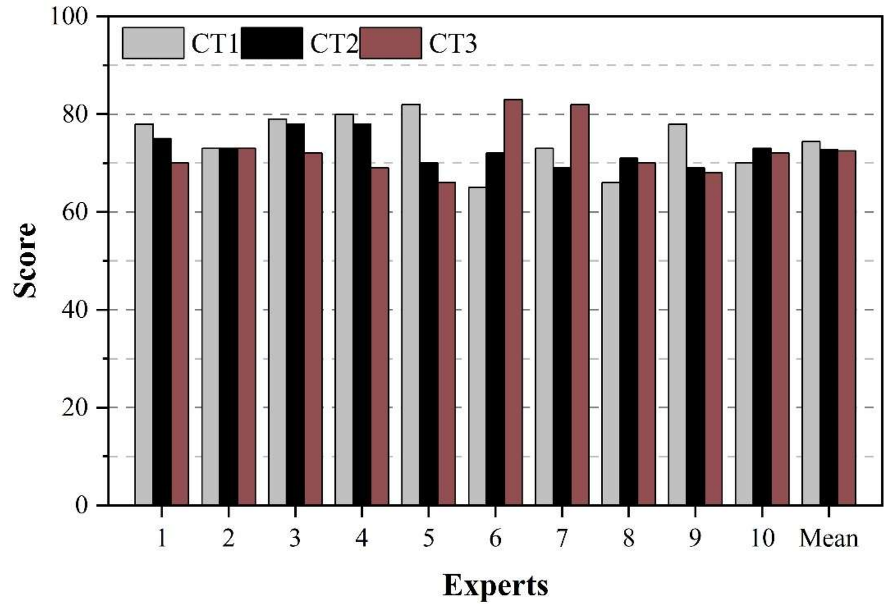

Fig. 9. The score of traditional art creation

In order to compare the differences between the two modes of art creation more clearly, this paper compares the scores of the works, and the comparison results of the two modes of art creation are shown in Table 3. From the comparison results, the overall average score of computer-assisted art creation based on this paper is 84.63 points, and the overall average score of traditional art creation is 73.23 points. The score of computer-assisted art creation based on this paper is 11.40 points higher than the score of traditional art creation, which shows that the effect of computer-assisted art creation based on this paper is better than that of traditional creation, and it can improve the expressive power and creative efficiency of art creation.

Table 3. The comparison of the two art creation modes

Mode	Artwork	N	Mean	Integrated average score
Computer aided	JF1	10	84.9	84.63
	JF2	10	84.8	
	JF3	10	84.2	
Traditional mode	CT1	10	74.4	73.23
	CT2	10	72.8	
	CT3	10	72.5	

6. Computer-assisted and digital media integration and development

This paper constructs an improved art pattern generation model of CycleGAN to optimize computer-aided art creation, and verifies the effect of its assisted art creation through experiments. On this basis, according to the previous research on the relationship between computer-assisted art creation and digital media technology, it further proposes the realization method and integration strategy of computer-assisted and computer-integrated development for digital art and cultural inheritance.

First of all, digital media as information technology continues to improve the realization and application of scientific and technological products, not only can retain the characteristics of traditional media technology for the efficient dissemination of information, but also use its own advantages of big data technology to provide people with traditional media technology can not reach the information content and form, to provide people with a richer and more efficient information experience. The characteristics of digital media and computer-aided art creation are highly compatible, providing a more efficient and broader communication channel for the dissemination of art works. At the same time, the interactivity of digital media provides a unique artistic expression for computer-aided art creation. In addition, because of the Internet technology, the application of digital media technology in the dissemination of information has a more efficient and convenient mode of work, and the intelligent technology can make the process of information dissemination does not rely on manual operation, but also because of this so that the content of the information content will not be disseminated because of human error problems. Under the support of digital media technology, the accuracy of information content and form can be effectively guaranteed. For the application of digital media technology for computer-aided art creation, art creators can utilize accurate information content for targeted content design, so as to ensure that the artistic sense of the design work at the same time, but also to ensure that the content of the work of art can be guaranteed. Therefore, digital media technology has not only changed the traditional way of creating art design, but also provides more innovative possibilities for computer-aided art creation.

On this basis, the integration of digital media technology and computer-aided development can be carried out in the following aspects:

1) Broaden the communication media of art practice works and enhance the creative efficiency of art practice.
2) Enrich the expression form of art practice and enhance the interactivity and sharing of art works.
3) Promote the continuous innovation of the creative concepts and ideas of artistic practice, break the conventional creative thinking and attract the attention of the audience, but also let them stay to watch, so that the concepts and ideas of artistic creation continue to innovate and broaden.
4) Change the relationship between art creation and art appreciation, the modern information technology in digital media technology can provide a convenient and highly operable human-computer interaction interface for art creation. Strong interactivity makes the boundaries between art practitioners and art appreciators, and the distance between art practitioners and appreciators greatly narrowed, and the position between art practitioners and appreciators has changed.

7. Conclusion

The application of computer technology in the field of art creation has become more and more extensive, and its integration with digital media technology provides more possibilities for art creation and cultural inheritance. Therefore, this paper firstly researches on computer-aided art creation, and constructs an improved CycleGAN art pattern generation model by introducing the attention mechanism.

In the pattern generation experiments, the overall loss value of the improved CycleGAN model in this paper varies between 0.65 and 1.80, which solves the problems of pattern collapse and gradient disappearance and is better than other methods. Moreover, the Loss curve of the model network architecture in this paper converges faster, and its SSIM and PSMR values are the best, and the generated patterns are better. In addition, in the overall performance of the model, the number of parameters, model size, and running speed under the improved CycleGAN model compared to the traditional CycleGAN model are reduced by 4.176M, 15.57MB, and 0.59s, respectively, and with compared to other models in the performance evaluation indexes in the best performance.

In the art creation comparison, the overall average score of the works of computer-aided art creation based on the improved model of this paper is 84.63, while the score of the works of traditional art creation is 73.23, which further proves the advantages of computer-aided art creation. At the end of the study, this paper analyzes the impact of digital media on computer-assisted art creation, and provides a direction for the integration and development of computer-assisted art creation and digital media.

About the Author

Jiachang Huang was born in Xianning, Hubei, P.R. China in 1990. He obtained a master's degree from Hubei Institute of Fine Arts. Currently, he is teaching at Wuhan Technology and Business University. His main research directions are digital media art visual design and visual research on traditional Chinese culture.

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