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Article

Technical Innovation and Cultural Inheritance of Digital Calligraphy Art Creation

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Abstract: With the development of computer vision and digitization technology, automated generation of calligraphic fonts with specific styles has become a hot spot of research. Aiming at the current problems such as the strict requirements on the preliminary data collection work in the process of digitalized Chinese character art creation, this paper proposes a generative adversarial network model based on structural constraints. The structural style generator, detail style generator and discriminator are used to generate, optimize and discriminate the images of calligraphic Chinese characters respectively, and finally complete the style migration to the target fonts. Analysis of the training and generation results of the model using the dataset reveals that, compared with other models, this paper's method, except for special and personalized fonts that lead to a lower recognition rate, the correct recognition rate of other fonts can be more than 70% or more, and at the same time, the digitized calligraphy art MOS value generated by the model focuses on the range of 7 to 9 points. Therefore, it can be considered that the method in this paper can simultaneously generate images of calligraphy fonts of multiple styles, and the different font styles do not affect each other, and the final generation of calligraphy fonts is also better than the existing font generation model.

Keywords: structural constraints; generative adversarial network model; Chinese character art; MOS value

1. Introduction

With the rapid development of science and technology, digital technology has had a profound impact in various fields, and the art field is no exception [1]. And then digital calligraphy as an emerging art form, through the use of computers and digital technology, can realize the rapid creation, editing and dissemination of calligraphy works [2-3]. The emergence of this new technology has triggered new thinking about traditional calligraphy, and has also led to new styles and ways of presenting traditional calligraphy [4]. As a treasure of Chinese culture, traditional calligraphy has profound historical and cultural connotations, but in modern society, the inheritance and development of traditional calligraphy are facing some challenges [5-6].

The creative process of traditional calligraphy requires a long time of training and sharpening, which is difficult to adapt to the fast pace of modern society [7]. At the same time, traditional calligraphy works in informationization, digital preservation and dissemination of certain “incompatible”, can not be well matched with the dissemination of digital media [8-10]. Therefore, the background of this topic is to explore the innovative application and influence of digital calligraphy in the field of traditional calligraphy, and to compare the similarities and differences between digital calligraphy and traditional calligraphy, with a view to promoting the innovation and development of the art of calligraphy, and fostering the integration of traditional culture and modern technology [11-13]. This selection aims to discuss the problems faced by traditional calligraphy and to provide new ideas and directions for the development of the art of calligraphy in the digital era.

In order to solve the problem that digital calligraphy art generation requires a large number of a priori Chinese characters in the preliminary data collection work. In this paper, a model for generating calligraphic Chinese characters based on structural constraint generation adversarial network is proposed.

The model is mainly composed of three parts: structure style generator, detail style generator and discriminator, with P4ConvZ2 convolutional network as the backbone. Firstly, the handwriting of Chinese characters extracted directly from the source print image is used as the structural condition to generate calligraphic Chinese characters. Then, the content features are obtained by the detail style generator through convolution operation to optimize the stroke details of the calligraphic Chinese characters and improve the quality of the generated calligraphic Chinese character images. Finally, the completeness and correctness of the structure of the images of calligraphic Chinese characters are judged. The collected stone carvings and calligraphic artifacts are used to build a dataset, which is compared with other classical generation algorithms, and the experimental results prove the effectiveness of the method proposed in this paper.

2. Digital Calligraphy Design Strategies

2.1. Technical Tools

Before font design entered the digital era, "Chinese fonts were generally written by workers with thin paper and pasted on lead blanks, engraved by carvers in accordance with the handwriting engraved, or photographic technology will be used to photocopy the handwriting on copper molds, engraved by carvers processed and engraved into the original characters, and then electroplating method to make copper molds, casting of lead characters." With the progress of China's level of industrialization, the word draft can be handed over to a specialized department to complete the machine engraving, even so, the process of font design is still complicated, a set of fonts cost quite high. Especially calligraphy fonts, calligraphers need to write out word by word, a set of calligraphy fonts need at least six thousand words, each word often need to be written three or five times, and some even dozens of times, the workload and the difficulty of quite a lot. After entering the digital era, fonts have become a digital file, designers can use graphic design software on the computer to carry out font design work, which greatly reduces the design workload of calligraphy fonts, the early word tools such as Adobe illustrator and Adobe Photoshop, etc., but these software can't be designed to deal with the fonts and packaging, there are greater limitations. However, these software cannot process and encapsulate the designed fonts. With the increasing degree of font design specialization, font design tools are emerging, professional font manufacturers will generally internal independent research and development of software to carry out font design and processing, in the market common font application tools including Fontographer and FontLab and other old font software, Robofont, TypeTool and other lightweight font editor, but also have a free FontForge like this because of the free font editor. FontForge, which is popular because it is free and open source.

2.2. Generalization of the Design Methodology

At present, from the perspective of design and development, there are three main methods of digitized calligraphy font design, namely, reproduction method, imitation writing method and broken type method. These three design methods are essentially based on the original calligraphy as a blueprint, through the designer of the original work of different dimensions, different scales of restoration.

2.2.1. Reproduction Method

Reproduction method, that is, the use of digital means, to a greater extent, the true restoration of the original font style and characteristics, faithful to the original font style, and some of the font design additions. Reproduction method is currently the most widely used method of design and development.

2.2.2. Imitation

Imitation method, that is, on the basis of the characteristics of the original calligraphy, imitating the style of the author to create writing, and then corrected through the design software. The imitation method is different from the reproduction method, because the imitation process adds the imitator's personal writing style and innovative insights, so compared with the original calligraphy there are some differences, but it has both the characteristics of the original calligraphy and the imitator's personal writing personality.

2.2.3. Type Breaking Method

Broken type method, that is, based on the style characteristics of the original calligraphy, a greater degree of design creation, through this method of designing fonts can also be called "design type calligraphy font". Although this calligraphy font design method draws on the characteristics of the original calligraphy, it has a strong personal style and contemporary characteristics. Regardless of the design method, digital calligraphy fonts should be standardized on the basis of inheritance of the original stylistic characteristics of the strokes, even if the personal style of the designers and creators is added in the design process, it is necessary to take the original calligraphy as the core of the aesthetic standard of calligraphy fonts.

2.3. Digital Calligraphy Font Design Process

In the late twentieth century, the Shanghai Zigzag Drawing Group developed a number of calligraphic fonts, including the New Wei Style, the Running Regular Style, and the Shu Tong Style, which played an important role in the field of Chinese typeface design at that time. The whole process of calligraphic font design by the drawing group of Shanghai Ziqi Factory No.1 can be divided into several parts, such as setting the character list, writing, selecting characters, and fixing. After determining the standard number of characters for the whole set of fonts, after the character list is determined, the calligrapher creates and writes the characters according to the requirements, and weighs the elements of pen shape, thickness, structure, etc., in artistry and functionality, and the characters can only go into the printing stage after the calligrapher and the drawing team select and modify the characters in a fine way. After digital technology has entered the field of font design, calligraphic fonts have been transformed into computerized font libraries, and the design process of calligraphic fonts has become more refined with the aid of digital technology. The design and development process of a digitized calligraphy font font product has eight steps, namely, collection of manuscripts, scanning of manuscripts, selection of glyphs, fine design, creation of complementary characters, checking of glyphs, review by experts, and encapsulation into a library.

3. Creative Methods for the Generation of the Art of Epigraphy

3.1. Problem Setting and Model Assumptions

The research objective of this paper generates images of calligraphic Chinese characters in different calligraphic styles of books. Assume a dataset D with N samples, part of which is paired image pairs:

$$D_t = \{(x_i, y_i)\}_{i=1}^{N_t} \tag{1}$$

That is, the pairs of Chinese character images of standard printing style and the corresponding images of calligraphic Chinese characters of target style, where $x_i \in X^D$ denotes the Chinese character images of the given standard printing style, and $y_i \in Y_{tg}^D$ denotes the images of calligraphic Chinese characters of target style [14]. The other part of the dataset has only images of Chinese character in standard printing style:

$$D_u = \{(x_i)\}_{i=1}^{N_u} \tag{2}$$

3.2. Generating Adversarial Network Models

In this paper, the method does not need to collect a large amount of a priori knowledge information about Chinese characters, and can be trained to generate structurally correct high-quality calligraphic Chinese characters by using only the handwriting of Chinese characters extracted directly from the source printed image as the structural condition. The block diagram of this method is shown in Fig. 1, where x_c is the image of a standardized printed Chinese character, x_{sk} is the skeleton image of the source Chinese character, y_s is the image of the calligraphic Chinese character in the structural style, and y_c is the image of the calligraphic Chinese character in the detail style.

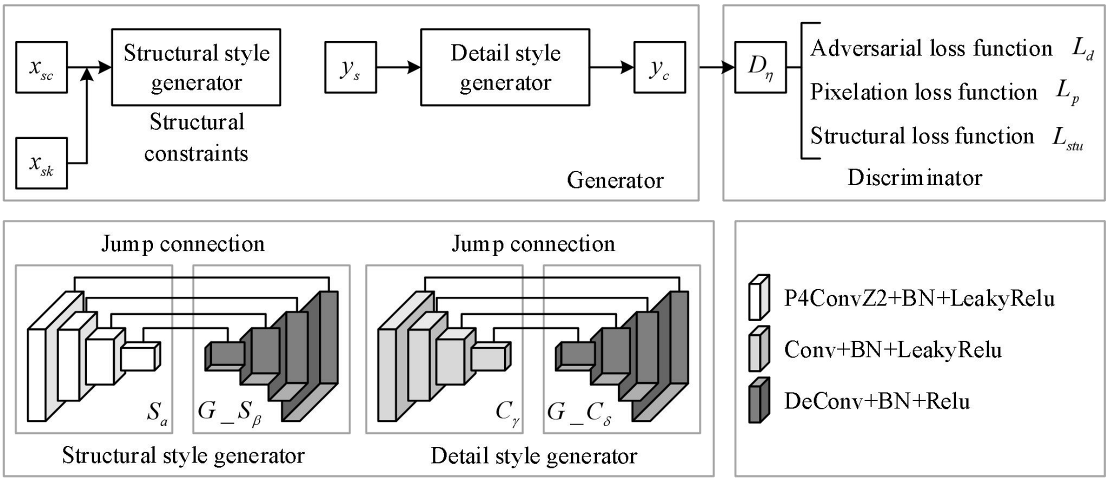

Figure 1. The framework diagram of the method proposed in this paper.

The method in this paper consists of 3 main parts: structure style generator, detail style generator, and discriminator D_η. The structure style generator consists of the resultant constructive feature extractor S_α and the structure style decoder G_S_β. The detail style generator consists of a detail feature extractor C_γ with a detail style decoder G_C_δ. The source printed Chinese character image is generated from the calligraphic Chinese character image by the structure style generator under the condition of structural constraints, so that the Chinese character image has the correct Chinese character structure. The detail style generator optimizes this Chinese character image and finally generates the calligraphic Chinese character image with correct structure and better quality.

3.2.1. Structure Style Generator

The dataset of calligraphic Chinese characters is small, in order to learn more structural features of Chinese characters, this paper introduces the group isovariant convolution structure in the structural feature extractor. Because the convolution kernel in the group isovariant convolution structure with four rotated filters leads to the incorrect structure of the image generated by the structural style decoder with problems such as rotational distortion, this paper proposes the introduction of the Chinese character structure map as a structural constraint, which is used to guide the model to generate the structurally correct Chinese characters for calligraphy.

In this paper, we extract the structure map of standardized printed Chinese characters through the skeleton extraction algorithm, which not only serves as the structural supervisory information of the Chinese characters, but also serves as the structural constraints of the Chinese characters in order to guide the model to generate structurally complete and correct calligraphic Chinese characters. Most of the current studies on the generation of calligraphic Chinese characters encode the a priori knowledge of the structure of Chinese characters and then introduce it into the model to generate calligraphic Chinese characters, and the a priori information of the Chinese characters often leads to an increase in the workload of data collection in the early stage. In this paper, the structural map of Chinese characters introduced in this paper is only based on the standard printed Chinese characters obtained through the Chinese character skeleton extraction algorithm, so the structural constraints used in this paper have little impact on the preliminary data collection work, which facilitates the extension of the experimental results.

Firstly, the input image x_{sc} of a printed Chinese character and the corresponding structural map x_{sk} of the Chinese character are passed through a structural feature extraction network to obtain the structural features by group isovariant convolution operation. Then the features are gradually up-sampled using the inverse convolutional layers, while the output of each inverse convolutional layer is jump-connected to the corresponding layer in the structural feature extractor for transmitting the low-level structural features. Finally, the structurally correct images of Chinese calligraphy characters y_s are generated by the structural style generator.

Structural Framework of the Structural Style Generator Structural Feature Extractor S_α has 4 network layers all using the same 5 × 5 group isovariant convolution kernel, an activation function

LeakyRelu with a slope of 0.2, and a batch normalization layer and with a step size of 4. Structural Style Decoder G_S_{β} has 4 network layers all using the same 5 × 5 inverse convolution kernel, a Relu activation function, and a batch normalization layer.

3.2.2. Convolutional Networks

Since calligraphic Chinese characters are written by calligraphers with brushes, the images of Chinese characters are more irregular compared to standard print, and calligraphic Chinese characters written by calligraphers vary even for the same radicals, this paper introduces a group isovariant convolutional network into the structural feature extractor to improve the structural feature extraction capability. The P4ConvZ2 convolution operation of the swarm isovariant convolutional network contains filters with four rotations, so the introduction of the swarm isovariant convolutional network is equivalent to data augmentation operation on the data, which somehow solves the problem of small dataset.The P4 swarm is a swarm consisting of rotational and translational transformations around the center of the square mesh at 90°. The elements of this swarm use 3 integers r, u, v, defined as:

$$g(r,u,v)=\begin{bmatrix} \cos\left(r\frac{\pi}{2}\right) & -\sin\left(r\frac{\pi}{2}\right) & u \\ \sin\left(r\frac{\pi}{2}\right) & \cos\left(r\frac{\pi}{2}\right) & v \\ 0 & 0 & 1 \end{bmatrix} \tag{3}$$

where $0 \le r < 4, (u,v) \in Z^2$ denotes the coordinates of the pixel points on the two-dimensional image Z^2.The binary operation of the P4 group is a matrix multiplication.The pixel points on Z^2 used by the P4 group are equal to the pixel points that are obtained by combining the matrix $g(r,u,v)$ with the points $(u^{'}, v^{'})$ by multiplying the chi-square coordinate eigenvector $a(u^{'}, v^{'})$, denoted as:

$$ga \approx \begin{bmatrix} \cos\left(r\frac{\pi}{2}\right) & -\sin\left(r\frac{\pi}{2}\right) & u \\ \sin\left(r\frac{\pi}{2}\right) & \cos\left(r\frac{\pi}{2}\right) & v \\ 0 & 0 & 1 \end{bmatrix}\begin{bmatrix} u \\ v^{'} \\ 1 \end{bmatrix} \tag{4}$$

3.2.3. Detail Style Generator

The image x_{sc} of a printed Chinese character and the corresponding structure map x_{sk} of this Chinese character are generated by a structure style generator to produce the image y_s . y_s , although it is the image of a calligraphic Chinese character with the correct Chinese character structure, there are still the problems of distortion of the calligraphic Chinese character strokes and blurring of the stroke boundaries in the image. Therefore, in this paper, we optimize the image y_s by detail style generator to improve the quality of the generated image.

Firstly, the generated image y_s is convolved by the detail style feature extractor to get the content features, and then up-sampled to the target resolution using the inverse convolution operation to generate the image y_c of the Chinese calligraphy characters. The detail feature extractor C_{γ} uses the same 5 × 5 convolution kernel, activation function LeakyRelu with a slope of 0.2, and batch normalization layer with a step size of 4. The detail style decoder G_C_{δ} uses the same 5 × 5 convolution kernel, Relu activation function, and batch normalization layer in its 4 layers. function and batch normalization layer.

The encoder-decoder architecture maintains the same properties of the input image and the output image. The detail style generator uses the encoder-decoder architecture to keep the Chinese character structure of the image y_c generated by the detail style generator unchanged, so that the Chinese character structure of the Chinese character image y_c is complete and correct. The detail style generator optimizes the generated image y_s of the structure style generator through the optimization objective function composed of adversarial loss function, pixel loss function and structural loss function to refine the details of the strokes of the Chinese characters in calligraphy, improve the quality of the character images of the Chinese characters in calligraphy, and ultimately obtain the high-quality target Chinese character images of Chinese characters in calligraphy with a complete and correct structure y_c [15].

4. Analysis of the Effects of the Creation of the Art of Epigraphy

4.1. Data Sets

Because there is currently no available public dataset for calligraphy text style migration, and most of the real-life calligraphic artifacts are orphaned cannot construct enough paired datasets for supervised training of the model. Based on this, this chapter produces datasets from collected stone carvings and calligraphy artifacts in order to more closely match the actual situation of text style migration. Finally, 1200 fonts of Yan Zhenqing, a Tang Dynasty calligrapher, 1200 fonts of Liu Gongquan, a Tang Dynasty calligrapher, and 1200 fonts of Zhao Mengfu, a Yuan Dynasty calligrapher, are selected through screening and comparison as the sample set to provide the target styles in the experiments of this chapter, and 1200 images of Song font are chosen for the sample set to provide the original content features in the experiments. The dataset image size sizes were all processed to 224 × 224 size, and then the dataset was divided into two parts, the test set and the training set, according to the ratio of 1:9.

4.2. Model Training

In the deep learning network in the image encoding and emotion extraction framework, the Adam function is used for optimization (the bata value is taken as 0.42), and the learning rate is taken as 0.0003. In the image generator and discriminator network, the RMSProp optimizer is used, and the initialization is carried out using the Xavier way during training. The change of loss function with the number of iterations during the training process of the generator adversarial network is shown in Table 1, and the experimental results show that the more complex the calligraphy font is, the more obvious the stylized features are, and the more difficult the potential features are to be captured, the more training iterations are required. In general, about 600 iterations of training can achieve better results.

Table 1. Training process of GAN.

Iteration number	Loss value(g_loss)	Loss value(d_loss)
0	-39.83425	-94.53039
100	-7.01657	-17.34807
200	-8.23204	-17.9558
300	-8.23204	-19.17127
400	-7.62431	-19.17127
500	-5.8011	-18.56354
600	-4.58564	-19.17127
700	-3.9779	-19.17127
800	-2.76243	-19.17127

4.3. Results of Calligraphy Generation

4.3.1. Generating Quality Evaluations

Currently there is a lack of common evaluation methods for both the calligraphic images and the results of generating adversarial models, in order to quantitatively evaluate the experimental effects, the initial distance (FID) is used as a measure to evaluate the results generated by the models proposed in the paper.The DR value denotes the probability that the generated calligraphic fonts can be correctly recognized, which is used to measure the accuracy of the generated fonts, and the MOS value denotes the human eye's subjective evaluation scores, which are used to measure the visual quality of the generated images. By selecting 10 images of each of the 8 styles of calligraphic fonts, randomly disorganizing them, and then conducting human eye subjective evaluation experiments in a normal light environment, each observer needs to recognize the image fonts and score the quality of the image (1~10, with the higher score representing the better visual quality of the human eye). In the paper, the average of the experimental results of 30 observers was finally selected as the final results, and the results are shown in Figure 2. The font types 1~8 are WeiBei, KaiShu, XingShu, XingKai, CursiveShu, ShuShu, LiShu and LiuShu, respectively. As can be seen from the figure, the recognition rate of various calligraphic fonts generated by the algorithm is higher than that of other comparative generation models, except for Cursive Script, Shu Style and other fonts with complex structure and strong personalization itself resulting in lower recognition rate, the correct recognition rate of other fonts reaches more than 70%, and for the calligraphy fonts of Clerical Script and Willow Style, which have clear and neat font frameworks and structures, the correct recognition rate is more than 90%.

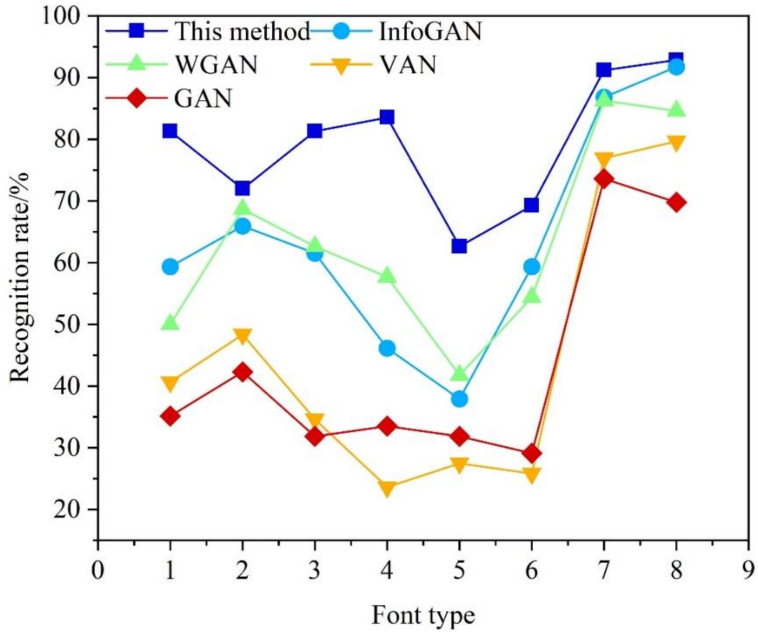

Figure 2. Comparison of recognition rate of generated characters.

In terms of visual quality, the comparison results of the MOS scoring results of the generated fonts are shown in Fig. 3, which shows that the MOS scoring results of the algorithm results in the paper are concentrated in the range of 7~10 points, which is much higher than the other comparative models, indicating that the generated images are in line with the observation characteristics of the human eye for the calligraphic images.

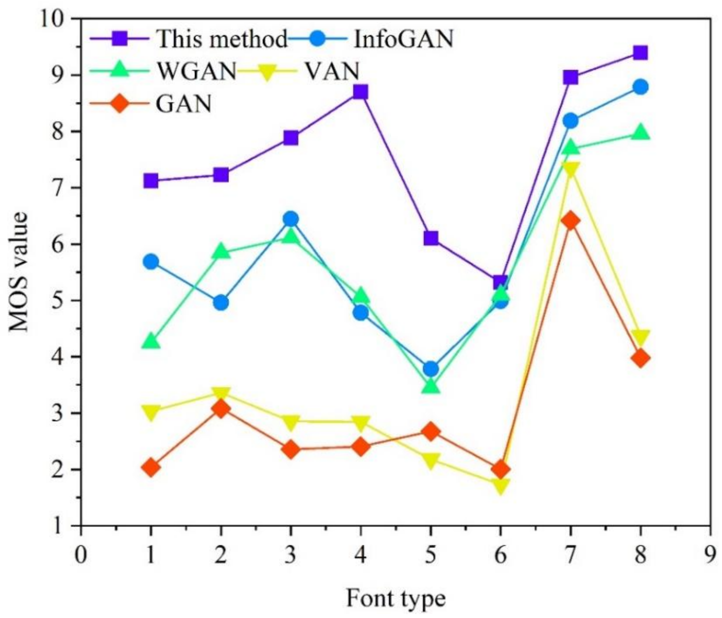

Figure 3. Comparison of mean object score for generated characters.

FID is used to measure 2 metrics of the GAN network by extracting features from the middle layer and then modeling the distribution of these features with a normal distribution:quality and diversity of the generated images.Lower FID means higher quality and diversity of the images. Compared to IS, FID has better robustness to noise.The comparative results of FID calculation are shown in Figure 4.

The FID calculation results of the algorithm in the figure are much lower than those of other models, which indicates that the algorithm in the text has significantly improved both the diversity and visual quality of the generated calligraphic fonts. Overall, the algorithm in the paper is not only able to generate calligraphy images of many different styles, but also has a high recognition rate and good image quality, which is especially suitable for the field of generating fonts with strong structure, such as Clerical Script and Liu Style.

Meanwhile, it is found that the image quality and recognition rate do not exactly correspond to each other, with the highest recognition rate of official script fonts but the best visual evaluation results of Liu style images, and the lowest recognition rate of cursive script fonts but the worst evaluation quality of Shu style images, which indicates that the human eye's viewing of calligraphy images does not completely depend on whether it can correctly recognize the fonts in the calligraphic works, and also further indicates the importance of the emotional styles in calligraphy in the calligraphy image generation and It also further demonstrates the importance of emotional style in calligraphy in the generation and study of calligraphy images.

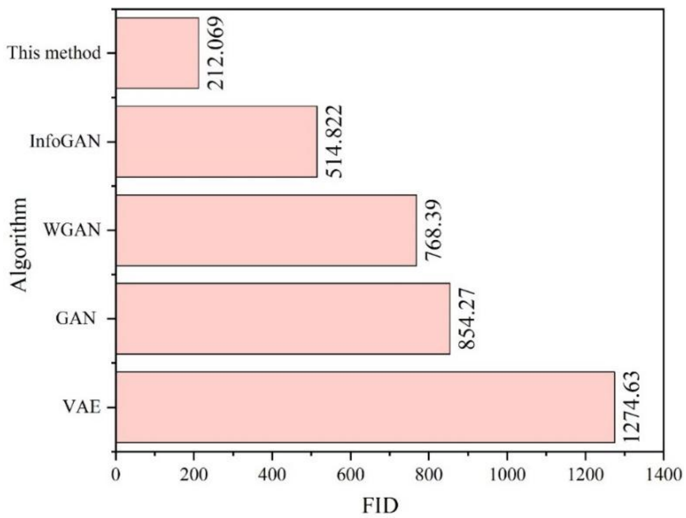

Figure 4. Comparison of FID results.

4.3.2. MOS (Mean Opinion Score) Evaluation

In this paper, the proposed algorithm is utilized for the complete generation of font library with Qigong and Wenzhengming fonts as an example. 7560 Qigong and Wenzhengming fonts have been experimentally generated, and the generated fonts have been manually judged using MOS metrics. Among them, 1~10 represent different font samples generated. The maximum score for each item is 5 and the minimum score is 0. The higher the score, the better the font is represented. Five calligraphy teachers and 10 evaluators with postgraduate degrees were asked to score the generated fonts separately, and the MOS value of each character was calculated, and the overall average score was used as the final score of the generated font library, and the results are shown in Table 2.

Table 2. MOS evaluation results.

Project	Example										Final score
Open font	1	2	3	4	5	6	7	8	9	10	……	
MOS value	3.89	3.74	3.82	3.86	3.92	3.89	4.00	3.90	3.93	3.93		3.888
Text font	1	2	3	4	5	6	7	8	9	10	……	Final score

MOS value	3.93	3.94	3.87	3.90	3.84	3.80	3.89	3.95	3.84	3.93		3.889

At the same time, the statistical analysis of the font as shown in Figure 5, this paper's algorithm generates fonts with good generation effect, more than the total number of generated fonts most of the font MOS scores more than 3 points, in line with the needs of practical applications.

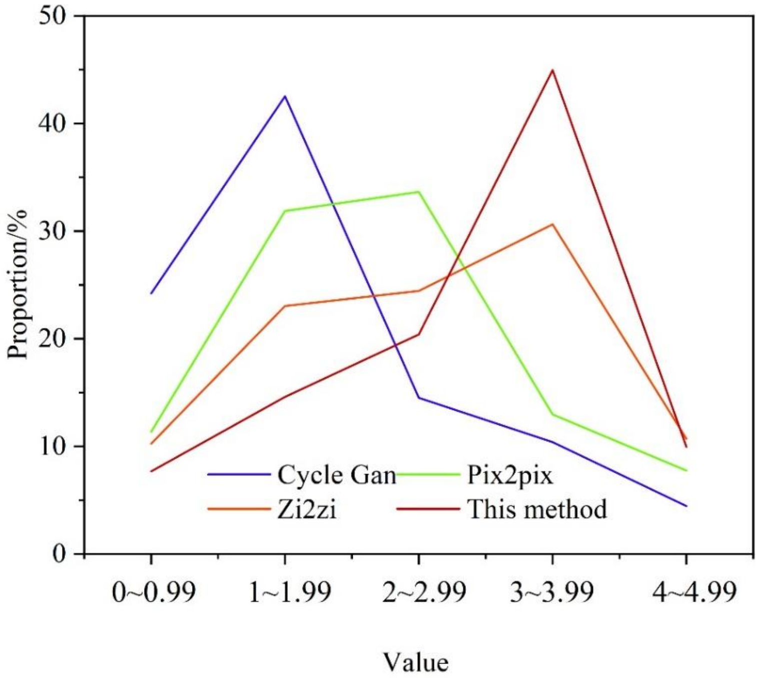

Figure 5. Example of failed font generation.

In addition, through the experiment of expanding the font library, it is found that the method of this paper still has shortcomings, and the example of the failure of generating fonts is shown in Table 3. When the font strokes are dense or the glyphs are complex, the network has difficulty in feature learning, and the generated fonts have a calligraphic style, but the details of the font strokes have fuzzy problems, so the network still needs to be improved in the generation of very fine font details.

Table 3. MOS statistics.

Project	Example															
Example	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
MOS value	3.22	3.16	2.89	3.06	3.26	2.83	2.89	2.82	3.16	3.78	2.70	3.16	3.06	3.11	2.78	3.14

5. The Role of Generative Creativity in the Transmission and Innovation of French Art

5.1. Digital Storage

Using generative artificial intelligence technology, large-scale data collection and digitization of Yunfeng carved stone calligraphy works can be carried out, which is able to record and preserve the cultural heritage of the surviving inscriptions, cliff carvings and other cultural heritage, and provide a basis for the restoration and reproduction of the inscriptions, cliff carvings and other inscriptions at a later stage. By analyzing and storing these data, a digital archive of Yunfeng stone carving calligraphy art will be established, providing a rich resource base for subsequent research, teaching and creation.

5.2. Stylistic Learning and Re-Creation

The generative artificial intelligence system is able to learn the stylistic characteristics of Yunfeng stone calligraphy of the Northern Dynasty and recreate fonts and graphics on this basis. This can more conveniently and intuitively help calligraphy art enthusiasts and learners to understand the character knots, strokes and chapters of Yunfeng stone-carved calligraphy, and it can provide creative inspiration and reference for calligraphy art researchers to promote the inheritance and development of Yunfeng stone-carved calligraphy art.

5.3. Calligraphy Educational Aids

Generative AI serves as an assistive tool that can demonstrate the characteristics of calligraphy, basic techniques, and textual content, enabling learners and enthusiasts to more intuitively understand the writing techniques and artistic characteristics, thereby improving the efficiency and quality of learning.

5.4. Sensitization and Promotion

Today, with the rapid development of the Internet and 5G, the use of generative artificial intelligence and other technical means to build a platform for the inheritance and innovation of the Northern Dynasty Yunfeng stone calligraphy art, the integration of calligraphy resources, materials, condensing the Yunfeng stone Chinese traditional cultural genes of the aesthetic category, through the historical gene decoding reconstruction of the contemporary cultural identity of the “concentric circles.

1. Condense the value symbols. Refine the representative cultural symbols from the political, economic, cultural, religious and other historical values of the Northern Dynasty Yunfeng stone calligraphy art, tap the shared value of Chinese cultural symbols, highlight the cultural value of Yunfeng stone calligraphy art, and form a nationally and even internationally recognized Yunfeng stone value symbols with strong recognition, establish brand awareness, such as the organization of Yunfeng stone calligraphy art related celebrations, Zheng Daozhao Commemorative activities, etc., to enhance the sense of cultural identity.

2. Expand the form of publicity. According to the prototype of the remains of the Northern Dynasty Yunfeng stone carving, combined with contemporary literature research, local records, ancient records, etc. for digital presentation, taking into account the needs of audience groups of different age groups, text, video, animation, games and other forms of presentation, the use of generative artificial intelligence to achieve the digital restoration of the Northern Dynasty Yunfeng stone carving calligraphy art, complement the weathering and mutilation of the part, simulation of the original engraving texture, archiving and retention, to achieve Scene reproduction; designers can select the Northern Dynasties Yunfeng carved stone in the typical inscription calligraphy font, extract the art of penmanship, stylistic layout, chapter rhyme and other characteristics of the font innovation design and create a font library, the creative process can also be based on their own experience of the art of calligraphy to further adjust and improve the formation of contemporary personalized calligraphy font of the Northern Dynasties Yunfeng engraved stone to strengthen the cultural memory.

3. Broaden publicity channels. On the basis of building WeChat, Tik Tok, Shutterbug and other multi-form publicity modes and platforms, build a government-community-residents synergistic network, and through subtle influence, explore the mechanism, action logic, inheritance mode, etc. of the community and the North Dynasty Yunfeng stone calligraphy art, so as to broaden the channels of inheritance and innovation of the North Dynasty Yunfeng stone calligraphy art. For example, the fonts created by using generative artificial intelligence are widely applied to posters, posters, books and other media in contemporary life, to community propaganda, community museums, network media, etc., to form intergenerational inheritance, and revitalized inheritance across time and space and across regions. Through the means of generative artificial intelligence, the unique artistic style and characteristics of the Northern Dynasty Yunfeng stone carving will be shown, and more people will be attracted to pay

attention to and appreciate the calligraphy art of the Northern Dynasty Yunfeng stone carving through the dissemination of the Internet, as well as inherit and innovate the calligraphy art of the Yunfeng stone carving, so as to iterate continuously, and to form a benign operation by cyclic repetition.

6. Conclusion

Aiming at the fact that existing models require a large number of a priori Chinese characters in the process of pre-data collection for generating images of Chinese calligraphy fonts, this paper carries out a study on the generation of Chinese calligraphy characters based on structural constraint generative adversarial networks. The source Chinese character images are used as structural constraints to generate high-quality calligraphic Chinese characters through the generative adversarial network model. Based on the dataset produced in this paper to complete the experiments and the comparative analysis of the experiments, MOS evaluation results show that the model in this paper in the cursive, Shu font type recognition rate of less than 70%, other fonts of the correct recognition rate of more than 70%, Clerical Script, Liuji, and other calligraphic fonts, the correct recognition rate of more than 90%. The MOS value evaluation results are much higher than other comparative models. The model in this paper has made progress in the quality and efficiency of calligraphic font generation.

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