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Generative Modeling-based Stroke Reconstruction of Calligraphic Seal Engraving and Design of 3D Virtual Display

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Abstract As an important carrier of Chinese culture, Calligraphy Seal Engraving carries deep historical and cultural connotations. In this study, we propose a generative model-based method for reconstructing calligraphic seal cutting strokes and designing 3D virtual display. The consistent point set drift (CPD) algorithm is used to match the stroke contour, combined with an autoregressive model to generate the calligraphic seal cutting texture, construct an asymmetric rhombic stroke model to characterize the strokes, and develop a 360-degree immersive 3D virtual display system. The experimental results show that the proposed method achieves 0.9437, 0.9531 and 0.9542 in SSIM, FM and S-measure, respectively, which are significantly better than the traditional OTSU method of 0.8165, 0.8596 and 0.8648. In the single dataset test, the proposed method obtains the best performance on 10 different inscriptions, among which the SSIM value of 0.9737 is achieved on the record of Miaoyanji Temple, and the SSIM value of 0.9542 is achieved on the record of Miaoyanji Temple. The SSIM value reaches 0.9765 and 0.9042 on the Shenzejun stele. The audience experience evaluation of the virtual display system shows an overall satisfaction score of 89.039, with the highest score of 89.912 for the narrative experience. Through the organic combination of stroke reconstruction and 3D virtual display, this method effectively realizes the digital protection and cultural inheritance of calligraphy seal cutting works, and provides a new technical path for the modernized display of traditional culture.

Index Terms Calligraphy Seal Cutting, Stroke Reconstruction, Generative Modeling, 3D Virtual Display, Consistent Point Set Drift Algorithm, Autoregressive Modeling

I. Introduction

Chinese culture has a long history, and one of the important carriers that bear the responsibility of cultural transmission is the Chinese calligraphy script [1]. After 5,000 years of history and culture, the calligraphic characters have evolved from oracle bone inscriptions, gold inscriptions, big seal scripts, small seal scripts, and clerical scripts to cursive scripts, regular scripts, and running scripts in the late Eastern Han Dynasty, which are not only important carriers of the past history, but also important proofs of the Chinese people's rich creativity and imagination [2], [3]. However, the art of calligraphy seal-carving, which is transmitted on rice paper and stone tablets, is easily damaged and lost, which affects the effective inheritance of Chinese calligraphy [4], [5]. Therefore, it is meaningful to utilize modern technology to reconstruct and generate Chinese calligraphy characters and display them virtually.

Chinese calligraphy characters are not only numerous, but also have many strokes and complex structures [6]. With the help of the Chinese character generation model, it is possible to generate the remaining calligraphic font images with the same font style and glyph characteristics by giving only a small number of reference samples [7], [8]. With the rapid development of deep learning technology, the research in the field of font generation has gradually iterated the traditional methods and shifted towards the direction based on deep learning, which has injected new vitality into the field [9], [10]. This technological change has provided more efficient and accurate tools for font reconstruction and promoted innovation and development in the field of font generation [11]. However, these generation methods have problems such as high sample size required for training, unclear outlines of the strokes of the generated fonts, and unclear font structure, which inevitably result in the phenomenon of reduced recognition and lack of stylistic aesthetics of the generated Chinese characters, and will greatly reduce the efficiency of the font generation technology in assisting the development of font libraries [12]-[15]. Therefore, the study and realization of the automatic generation technology of calligraphy seal cutting strokes not only has important scientific research value, but also has far-reaching significance for the inheritance of calligraphy culture and the promotion of the development of related industries [16], [17].

Calligraphy seal cutting is an important part of Chinese culture, which contains rich historical and cultural connotations and artistic values. Traditional calligraphy seal cutting works face problems of physical media aging, color fading and structural damage during long-term preservation, which seriously affects the inheritance and development of this valuable cultural heritage. At the same time, the traditional display method mainly relies on static two-dimensional display, which is difficult to fully reflect the artistic charm and cultural connotation of calligraphy and seal-carving works, and unable to meet the diversified needs of modern audiences for cultural experience. The rapid development of computer technology provides a new opportunity for the digital conservation and innovative display of calligraphy seal cutting. Through digital technology, not only can we permanently preserve the morphological characteristics and artistic details of seal carvings, but also create an unprecedented immersive cultural experience for the audience through three-dimensional virtual reality technology. As the basic element of calligraphy seal cutting, the precise reconstruction of strokes is the key link in digital preservation. Traditional stroke extraction methods often rely on manual operation, which is not only inefficient, but also difficult to ensure the consistency of extraction quality. Stroke reconstruction techniques based on generative models can automate stroke extraction and characterization, greatly improving processing efficiency and accuracy. Texture is an important feature that reflects the writing technique and artistic style in calligraphy and seal cutting works, and the traditional texture synthesis methods have high computational complexity and limited effect. The autoregressive model provides a new idea for texture generation, which can effectively simulate the texture characteristics of calligraphic seal cutting. The development of 3D virtual display technology enables the audience to view the works from multiple perspectives in the virtual environment, obtaining richer visual experience and cultural feelings.

Based on the above background, this study proposes a complete set of solutions for digital reconstruction and virtual display of calligraphic seal cutting. First, a consistent point set drift algorithm is used to realize the accurate alignment of calligraphic characters with reference fonts, and the geometric features of the strokes are extracted by constructing an asymmetric rhombic stroke model. Second, the texture features are modeled using an autoregressive model to realize the automatic generation and control of calligraphic seal cutting texture. Finally, a 3D virtual display system based on 360-degree immersive interaction is developed, combining emotional design concepts and Gestalt psychology principles to create a viewing experience rich in cultural connotations. Through the organic combination of a series of innovative technologies, this study provides a new technical path for the digital preservation, artistic innovation and cultural inheritance of calligraphy seal cutting, which is of great theoretical value and practical significance for promoting the development of traditional culture in the digital era.

II. Stroke Reconstruction Generation Model for Calligraphic Seal Engraving

II. A. Stroke Extraction for Calligraphic Characters

Stroke extraction of calligraphic characters refers to extracting each stroke of calligraphic characters and recognizing the stroke categories. In this paper, we draw on the ideas of previous authors in stroke extraction, and utilize the reference Chinese character outline for point set alignment to get the correspondence between the pixel points of the calligraphic character and the reference Chinese outline, and then obtain the strokes and stroke categories of the calligraphic character.

II. A. 1) Consistent Point Set Drift (CPD) Algorithm

In computer vision, point set alignment technique is to find the spatial transformation process that aligns two point sets [18]. Commonly used point set alignment techniques include ICP, RPM, KC and CPD. Considering the large deformation of Chinese character outline point sets, this paper adopts CPD for point set alignment of stroke outlines.

The CPD algorithm transforms the point set matching problem into a probability density estimation problem. Given two point sets X and Y, which have contains N and M points respectively, a hybrid Gaussian model is constructed centered on the points in point set Y, and point set X is regarded as the data points generated by this model. The hybrid Gaussian model can be expressed as follows:

$$p(x)=\sum_{m=1}^{M}P(m)p(x\mid m) \tag{1}$$

Among them:

$$p(x\mid m)=\frac{1}{(2\pi\sigma^2)^{D/2}}\exp(-\frac{(x-y_m)^2}{2\sigma^2}) \tag{2}$$

D is the dimension of the points in the point set. Consider the case where the elements of the two point sets are not equal, i.e. there is noise. At this point, an additional uniform distribution is introduced and the two distributions are weighted using a parameter ω. The final hybrid Gaussian model is as follows:

$$p(x)=\sum_{m=1}^{M+1}P(m)p(x\mid m)=\omega\frac{1}{N}+(1-\omega)\frac{1}{M}p(x\mid m) \tag{3}$$

Assume that each data point is independently and identically distributed, when the likelihood function is:

$$L(\theta,\sigma^2)=\prod_{i=1}^{N}\sum_{m=1}^{M+1}P(m)p(x_i\mid m) \tag{4}$$

By maximizing the likelihood function it is possible to obtain the required parameters and thus the transformation relation, although the direct solution to the likelihood function is very complex, so the EM algorithm is used to solve the problem.

II. A. 2) Stroke Extraction and Stroke Profile Optimization

After the stroke semantic segmentation process in the previous section, we have been able to get the approximate correspondence between the strokes of calligraphic characters and the reference Chinese characters. According to the semantic segmentation results, the outlines of the same category of strokes are extracted one by one and matched using CPD. According to the matching result, we calculate the distance from the outline point of each Chinese character to be extracted to the outline of the reference font, calculate the nearest outline point of the reference font, and then use the strokes where the outline point is located as the stroke category of the Chinese character to be extracted, so as to categorize the outline points and obtain the complete stroke image.

II. B. Stroke Extraction of Calligraphic Characters

The extraction of strokes is conducive to a more in-depth analysis of calligraphic character styles, and this paper proposes an automated method for extracting simple strokes according to the research needs, firstly, to determine all the reference font stroke information, and using the matching information in the previous section, to establish the mapping from the midpoints of the strokes of the reference fonts to the centroids of the strokes of the calligraphic characters, and based on these stroke centroids, to further determine the strokes of the calligraphic characters.

II. B. 1) Stroke model construction

In general, the brush strokes are approximately in the shape of a water drop, and most of the brush stroke models are constructed around the water drop model, but this model is relatively complex in extracting the strokes, and cannot be applied to the morphologically diverse calligraphic glyphs. Therefore, in this paper, the brush stroke model is constructed as an asymmetric rhombus as shown in Fig. 1, and described using five parameters, i.e., the coordinate point $O(x,y)$ of the center position of the brush stroke, the unilateral width L_S, the distance from the front end of the brush stroke to the center of the brush stroke L_t, and the distance from the back end of the brush stroke to the center point of the brush stroke L_d.

This model structure is relatively simple, the stroke information is easy to extract, and the experimental results prove that this stroke structure can maintain the original stroke body structure morphology.

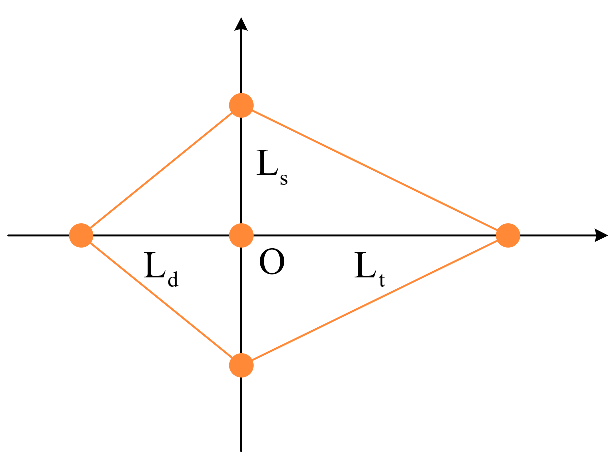

Figure 1: Stroke model

II. B. 2) Extracting stroke position parameters

In this paper, we label the stroke positions of the 28 standard strokes of the italic script, determining the number and position of strokes for each stroke, and possibly reducing the number of strokes. Before determining the stroke positions of calligraphic characters, we have determined the stroke positions of all Chinese characters in the reference font (italic). In this paper, we have pre-determined all the strokes of the commonly used Chinese characters in italics, and for each italicized stroke, we use the corresponding labeled strokes to match the contour and establish the transformation relationship between the two, after which the positional coordinates of the standard strokes are transformed.

However, in practice, it is found that the morphological structure of different italicized strokes is not exactly the same, which makes the outline points cannot be matched completely, and the transformed stroke position cannot reflect the morphological trajectory of italicized strokes well. Therefore, we directly replace the original strokes with the transformed standard strokes, which will make the italicized Chinese characters a little bit incongruous. However, in the actual experiment, we found that this phenomenon does not affect the effect of the reference fonts, and it is easier to establish the transformation relationship from italic to specific styles of fonts due to the unification of the morphology of italic strokes.

After determining the positions of the regular strokes of all reference fonts, we utilize the same idea, but instead of using the basic strokes, we directly use the corresponding reference font Chinese characters to match the stroke outlines. Generally the outlines are difficult to match due to the large difference in morphology, which is one of the reasons for optimizing the glyphs of calligraphic characters in the previous section.

II. B. 3) Extracting Stroke Morphological Parameters

According to the stroke model in this paper, after determining the stroke position, we only need to determine three more morphological parameters to get the complete stroke information. In fact, the information of the stroke also includes the direction, but the direction can be obtained by using the positional coordinates of the stroke. When the stroke morphological parameters are obtained, the stroke information of each stroke is calculated separately in order to improve the accuracy.

The stroke morphology parameters are calculated as shown in Fig. 2. According to the front and back stroke positions to determine the stroke direction, and then along the vertical direction to obtain the distance to the edge of the glyph as L_S, according to the parameters of the actual stroke, it is found that the three morphology parameters meet a certain relationship, L_S is about 1/2 of L_t, and and L_d is almost equal. For simplicity, this paper makes $L_d = L_S$, makes $L_t = 2L_S$, and then adjusted according to the actual situation.

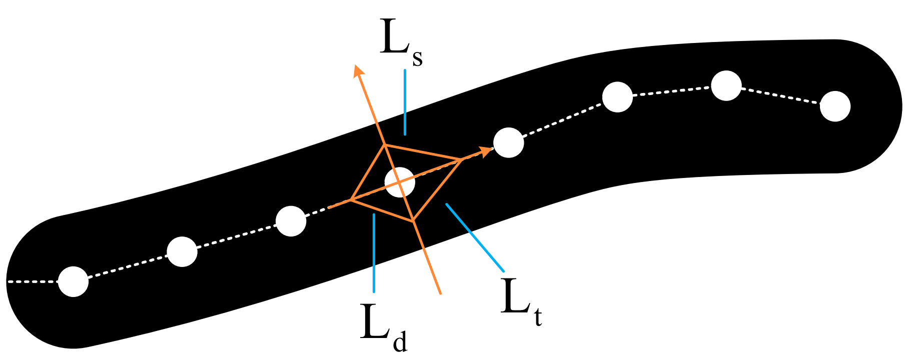

Figure 2: Sketch of the calculation method of stroke shape parameters

II. C. Texture Generation Model for Calligraphy Seal Engraving

II. C. 1) Constructing a Stroke Texture Library

In this section, the Regular Script is used as an example for the elaboration of the generation of calligraphy and seal cutting. In the process of calligraphy creation, the calligrapher is extremely concerned about the technique of running the brush and using ink, and is able to borrow the intensity and dryness of the ink color to show changes in the vivid effect of the strokes. When the pen dipped in full ink straight to write, then the pen head ink and moist, written out of the point of painting round and full continue to write, the amount of ink in the pen head due to be absorbed by the paper and gradually reduced, slowly ink dry state, written out of the edge of the point of painting and the inside of the ink due to the uneven distribution of rich changes in the texture of the strokes effect If this time the pen speed faster, the point of writing will be mixed with a trace of blankness, presenting the “Flying white” effect. Through careful study of the previous Regular Script works and according to the characteristics of Regular Script texture, we selected nine stroke textures with different ink color concentration and typical flying white effect from the Regular Script works, constructed a Regular Script texture sample library, and numbered them $T_i(i=1,2,...,9)$ according to the variation of concentration and flying white effect.

II. C. 2) Autoregressive models

Autoregressive model is an important model used in time series analysis and signal processing [19]. Usually, the mathematical expression of the autoregressive model is defined as follows:

$$x(n)=w(n)-\sum_{k=1}^{p}a_k x(n-k) \tag{5}$$

Here $w(n)$ is generally Gaussian white noise, a_k is the autoregressive coefficient, and p is referred to as the order of autoregression. The key to the autoregressive model is the calculation of the autoregressive coefficient. In this paper, the autoregressive coefficients are estimated using the Burg (Burg) algorithm [20], [21]. Its basic idea is to make a least squares estimate of the forward and backward errors of the data. That is, when the order is k, it is assumed that $e_k^f(n)$ and $e_k^b(n)$ represent the forward and backward prediction errors, respectively, i.e:

$$e_k^f(n)=x(n)+\sum_{i=1}^{k}a(i)x(n-i) \tag{6}$$

$$e_k^b(n)=x(n-k)+\sum_{i=1}^{k}a(i)x(n+k+i) \tag{7}$$

a_k by minimizing the mean of the forward and backward errors, i.e., calculating the minimum value of the following equation:

$$\varepsilon_k=\frac{1}{2}(\varepsilon_k^f+\varepsilon_k^b) \tag{8}$$

Get:

$$\varepsilon_k^f=\frac{1}{(N-k)}\sum_{n=k}^{N-1}|\varepsilon_k^f(n)|^2 \tag{9}$$

$$\varepsilon_k^b=\frac{1}{(N-k)}\sum_{n=0}^{N-1k}|\varepsilon_k^b(n)|^2 \tag{10}$$

$$a_k(i)=\begin{cases}a_{k-1}(i)+r_k a_{k-1}(k-i), & \text{When } i=1,...,k-1\\ r_k, & \text{When } i=k\end{cases} \tag{11}$$

Here r_k is the autocorrelation coefficient. Substituting Eq. (11) into Eq. (9) and Eq. (10) yields iterative expressions for forward and backward error estimation:

$$\varepsilon_k^f(n)=\varepsilon_{k-1}^f(n)+r_k\varepsilon_{k-1}^b(n-1) \tag{12}$$

$$\varepsilon_k^b(n)=\varepsilon_{k-1}^b(n-1)+r_k\varepsilon_{k-1}^f(n) \tag{13}$$

Here:

$$\varepsilon_0^f(n)=\varepsilon_0^b(n)=x(n) \tag{14}$$

In order to compute r_k, the k nd order prediction error expression is derived and made to have a value of zero so that r_k can be computed from the following equation:

$$r_k=\frac{-2\sum_{n=k}^{N-1}\varepsilon_{k-1}^f(n)\varepsilon_{k-1}^b(n-1)}{\sum_{n=k}^{N-1}|\varepsilon_{k-1}^f(n)|^2+|\varepsilon_{k-1}^b(n-1)|^2} \tag{15}$$

In addition, the autoregressive model has to use some numerical methods to determine the value of order p, such as the classical Akaike information theory (AIC) criterion. In order to reduce the amount of computation, in this paper, according to the experience of this paper, p takes the value of 3/4 of the sample texture length can achieve satisfactory results.

II. C. 3) Autoregression-based texture generation for calligraphic seal cutting

For a sample texture T_i in the texture library, it can be viewed as consisting of a set of texture units $g_j(j=1,...,h)$, (h being the height of the sample texture image). A sample texture is then considered to be composed of such a set of gray value change curves. For the gray value variation curve of texture units, it is regarded as a random sequence, and the autocorrelation coefficient between the gray values is found out by using Burg's algorithm. In this way the new regular script seal-engraving texture can be iteratively generated by Eq. (5).

II. C. 4) Stroke texture width control

In the process of calligraphy and seal carving, the width of the strokes expressed varies greatly due to the differences in pressure and direction applied to the brush as a result of movements such as lifting, pressing, pausing and turning.

Assuming that the width of the sample texture is w_s and the scaling factor of the texture width is f, the required texture width is w_r, i.e. $w_r = w_s * f$. If $f<1$, the sample texture needs to be scaled down by f. Cursive texture is mostly “flying white”, which has certain structural characteristics. Since the image scaling process can easily cause texture distortion and cannot maintain the original features of the texture, in order to make the newly generated brushstroke texture maintain its structural features, we introduce the stratified sampling method in statistics, and extract the texture units with the ratio of f from the sample texture A to form the new texture, instead of using the simple geometric transformation method of the image. Our method first counts the sum of the gray values of each texture unit $g_j(j=l,\cdots,h)$ of a sample texture G_{sum}, so as to obtain a histogram reflecting the gray variation of the sample texture, and then calculates the minima on this histogram, i.e., the first-order derivative f_d and the second-order derivative s_d of each point, and the minima should satisfy both $f\_d=0$ and $s\_d>0$. With the help of these minima, the sample texture is divided into n intervals $A_i(i=1,...,n)$, such that $w_s=\sum_{i=1}^{n}A_i$. The texture of each interval has similar characteristics, and then the texture units $S_i, S_i = A_i * f$ are randomly sampled from each interval with a ratio of f such that the new texture obtained from sampling is $w_r=\sum_{i=1}^{n}S_i$.

If $f>1$, i.e., the sample texture needs to be enlarged in proportion f, then this paper still adopts the stratified sampling method given above to sample texture units from the sample texture with a proportion of f times and insert them into the original texture. In order to maintain the structural characteristics of the texture, the insertion position of the sampled texture unit is behind the texture unit with the same serial number in the sample texture.

II. C. 5) Stroke Texture Extension

The traditional approach is to use texture synthesis methods, such as Markov's method to find similar pixel points or texture blocks for collocation from the image space of the sample texture. However, this method is computationally intensive, and in order to find matching pixel points or texture blocks, it is necessary to search through the entire image space of the sample texture. In this paper, the texture is modeled using an autoregressive model, so texture lengthening is easy to implement. Assuming that the length of the sample texture is L and the length of the required texture is R, the autocorrelation coefficient of the sample texture can be obtained by Burg's algorithm, and then the sample texture can be extended to R according to equation (5).

III. Design of Calligraphy Seal Carving Virtual Display System

This chapter takes 360-degree immersive interactive experience of calligraphy seal cutting as the design goal, and uses the roaming pavilion and particleization system as the spatial model to create a web-based new media three-dimensional interactive design product. The system can not only focus the visual perceptual attention to obtain the aesthetic perception of the shape and evolution of Chinese characters, but also experience the release of fun and emotion of the original imagery brought by dynamic calligraphy seal cutting. The specific framework of the system is shown in Figure 3. It is divided into three parts: scene modeling, calligraphic seal-carving font design, and imagery movement effect design.

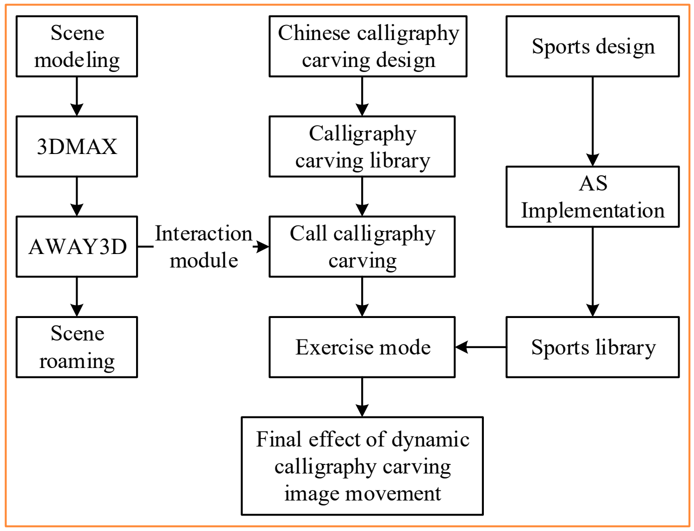

Figure 3: The system concrete framework schematic

III. A. Scene Modeling

The visualization of Chinese calligraphy based on Chinese characters follows the concept of human-centered emotional design. Emotional design is a kind of perceptual design concept. Donald A. Norman, a cognitive psychologist famous for his research on emotional design, once made this general evaluation of successful design works: profoundly analyzing the emotions and incorporating them to realize the unity of aesthetics and practicality. His theory of instinct, behavior, and reflection requires that the designer's product can bring the user sensory stimulation in appearance, produce a sense of achievement and pleasure in the process of using it, and produce resonance in the heart caused by emotion, consciousness, understanding, personal experience, and cultural background.

The behavioral layer design of the dynamic calligraphy seal-carving visualization demonstration system is reflected in the interaction between human beings and “paintings”, which governs human beings to interact freely and dynamically in the virtual environment through human subjective desire for knowledge and playful impulses. The reflective layer design is reflected in the aesthetic pleasure after viewing the dynamic seal-carving works, which is organically combined with the utilitarian demands.

III. B. Dynamic effect design

The “Gestalt” theory of visual perception emphasizes “perfect form”, where the human perceptual system has a strong tendency and preference for certain special forms. The idea that the observer perceives reality is called the mental field, and the perceived reality is called the physical field. The Gestalt school of psychology puts forward the theory of mind-object isomorphism, in the process of receiving and perceiving external information, the subject's mind is not passively reflecting the objectivity, but is actively organizing the information in a way that tends to “complete” the overall perception of things. The imagery movement of dynamic calligraphy and seal carving works is the external physical force, which can cause the inner psychological force of the appreciator, and thus heterogeneous isomorphism occurs. Imagery and imagination with vitality naturally appear in the vision, which in turn triggers other perceptions to have a unifying reaction and stimulates human psychological emotion.

Using ActionScript 3.0 programming language based on sound-driven visualization of dynamic calligraphic seal-carving imagery. According to different calligraphy seal-carving works, different music rhythms are adjusted, so that the movement reflects different emotional imagery. The emotion of joy and happiness will automatically appear in warm colors on the font, and the emotion of sadness and separation will automatically appear on the relative Chinese characters.

IV. Analysis of experimental results

IV. A. Generation effect analysis

In this paper, we take 10 inscriptions of calligraphy seal carvings as an example, 20% of each work totaling 1564 images are selected to form a training set, 5% of the dataset totaling 391 images are used as a validation set, and the rest totaling 5865 images are used as a test set.DnCNN, Unet, and the methods proposed in this paper train the network in the training set, and the OTSU does not need to be trained, in order to ensure the fairness of the comparison experiments, the training of the neural network including the number of iterations and learning rate and other hyperparameters are set the same, and finally generate the effect map in the test set and compare the FM value, SSIM and S-measure of each method, and finally get the results as shown in Table 1, which shows that the FM value, SSIM and S-measure are basically the same in the comparison of different methods.

Further more, this section divides the training set and test set randomly in each tablet work respectively, due to the small amount of data of a single tablet, this chapter randomly selects 80% of the data volume on each tablet work as the training set and the remaining 20% as the test set respectively, and finally calculates the average SSIM value in the test set, and the results obtained are shown in Table 2, in which A~J stand for the Large Character Yin Fu Sutra, Duo Bao Pagoda Stele, respectively, Huadu Temple Stele, Jucheng Palace Stele, Xuanxie Pagoda Stele, Myoan Temple Record, Sanmen Record, Shenzejun Stele, Yanle Ritual Stele, and Yanta Sacred Preface of Seal Scripts in 10 pairs of calligraphic seal-engraving works.

As seen from the results in Table 1, the three indicators of the traditional method OTSU are the lowest among all methods, the network proposed in this paper reaches the best numerical results so far, and the effect can be further improved if the training data is increased, and this chapter takes only a very small part of the data for training in order to simulate the real-life scenarios. Because in real life, the tablets are often difficult to collect, and after the collection of tablets, but also spend a huge amount of manpower and resources to label the samples, in order to be processed into the neural network needs the data style, if a data set only need to label 20% of the data, the rest of the algorithm can automatically learn and deal with it, you can get the best results at present in addition to the artificial labeling, the cost is still acceptable.

From the results in Table 2, it can be seen that the difference between different inscriptions is relatively large, the inscriptions with simple backgrounds can already be well processed by using OTSU, such as the large character yin fu jing and san men ji, and the difference in the results after processing of the five methods is very small, and the numerical results of OTSU to some extent reflect the complexity of the background, and the results have a negative correlation with the degree of complexity. When the background of the inscriptions is more complex, the difference between the different methods after processing is larger, the more complex the background, the greater the enhancement of Unet and the algorithm proposed in this paper compared with the traditional methods, the network proposed in this paper achieves the best results on 10 inscriptions, and there are different degrees of leadership compared with Unet, which is enough to show its great superiority.

Table 1: Comparison results in the total dataset

Method	SSIM	FM	S-measure
OTSU	0.8165	0.8596	0.8648
DnCNN	0.8536	0.8834	0.8824
DnCNN+OTSU	0.8795	0.8915	0.8979
Unet	0.9168	0.9384	0.9425
Ours	0.9437	0.9531	0.9542

Table 2: Comparison results in the total dataset in single dataset

	OTSU	DnCNN	DnCNN+OTSU	Unet	Ours
A	0.9826	0.9816	0.9837	0.9845	0.9857
B	0.9125	0.9063	0.9134	0.9389	0.9435
C	0.7426	0.7296	0.7546	0.8325	0.8796
D	0.9122	0.9056	0.9204	0.9489	0.9624
E	0.8526	0.8499	0.9062	0.9213	0.9349
F	0.9152	0.9245	0.9286	0.9542	0.9765
G	0.9805	0.9836	0.9799	0.9842	0.9868
H	0.6213	0.6245	0.6384	0.8684	0.9042
I	0.6925	0.6985	0.8014	0.9163	0.9386
J	0.8056	0.8124	0.9241	0.9386	0.9587

The gap between different works such as the background and font of the inscriptions is large, this section can use different works to test the generalization ability of the model, using only the 1068 images of the two works of the Large Character Yin Runes Scripture (A) and the Sacred Preface of the Wild Goose Pagoda (J) as the training set, the remaining 248 images of the two works as the validation set, the training model and the selection of the optimal model are only involved in the images of the two works, and the remaining 8 images of the works are used as the test set to test the generalization ability of the model, and the results are shown in Table 3.

Observing the results in Table 3, comparing with Table 1, it can be seen that there is a decrease in the model effect, SSIM, FM and S-measure mean values from 0.9437, 0.9531 and 0.9542 from to 0.8796, 0.8957 and 0.8947, a large decrease, on the one hand, the training utilizes the two works of the image background is simpler, and can achieve very good results, the After removing these two works, the average result naturally decreases. What's more, the images in the test set are very different from the training set, and some of the background contamination is small and simple, such as the large character Yin Fu Jing and the Yan Ta Sacred Teaching Preface, the model proposed in this paper can handle them very well, and achieve better results, the average values of SSIM, FM and S-measure are 0.9625, 0.9764 and 0.9678, respectively, which are almost the same as that of the previous comparison test.

Table 3: The generalization ability of the test model

Method	A+J			Average of the rest workpieces		
	SSIM	FM	S-measure	SSIM	FM	S-measure
OTSU	0.9256	0.9263	0.9158	0.8145	0.8559	0.8649
DnCNN	0.9341	0.9185	0.9215	0.8232	0.8612	0.8627
DnCNN+OTSU	0.9387	0.9289	0.9325	0.8548	0.8857	0.8829
Unet	0.7569	0.7893	0.8054	0.7659	0.8204	0.8342
Ours	0.9625	0.9764	0.9678	0.8796	0.8957	0.8947

Table 4: Evaluation index system for 3D virtual display experience of calligraphy carving works

Target layer	Criterion layer	Index layer
3D virtual display of Chinese calligraphy carving works	Narrative experience	Narrative animality
		Narrative accuracy
		Narrative attraction
		Narrative richness
		Narrative coherence
		Narrative substitution
		Narrative interest
		Narrative nonlinearity
		Narrative memorability
	Emotional experience	Novelty
		Sense of discovery
		Satisfaction
		Pleasure sense
		Sympathetic sense
		Comfort
		Sense of manipulation
	Sensory experience	Environmental authenticity
		Interface clarity
		Dubbing comfort
		Background music immersion
		Device prompt note
		Visual immersion
		Information accuracy
		Tactile perception
	Cognitive experience	Knowledge learnability
		The whole and part
		System applicability
	Interactive experience	Interactive learnability
		Prompt clarity
		Feedback rationality
		Interactive interest

IV. B. Audience experience analysis of virtual display

After completing the design of 3D virtual display of calligraphy seal cutting works, in order to understand the audience's experience of 3D display of calligraphy seal cutting, this paper adopts the hierarchical analysis method to construct the experience evaluation index system of 3D virtual display of calligraphy seal cutting works according to related literature as shown in Table 4. In this paper, the audience's experience evaluation of the 3D virtual display of calligraphy seal cutting works is divided into five dimensions: narrative experience, emotional experience, sensory experience, cognitive experience and interactive experience. A more detailed division is carried out under each guideline layer index.

Since the importance of each experience evaluation factor to the system evaluation is different, it is necessary to determine the weights of each evaluation factor, and the weights are determined using the secondary selection comparison method. Take the five categories of experience, namely narrative experience, emotional experience, sensory experience, cognitive experience and interactive experience, for example, to determine the weights of each major category and each indicator, and the weights of the evaluation indicators are shown in Table 5.

Table 5: Evaluation index weight for 3D virtual display experience of calligraphy carving works

Target layer	Criterion layer	Weight	Index layer	Weight	Total weight
3D virtual display of Chinese calligraphy carving works	Narrative experience	0.295	Narrative animality	0.129	0.0381
			Narrative accuracy	0.086	0.0254
			Narrative attraction	0.142	0.0419
			Narrative richness	0.092	0.0271
			Narrative coherence	0.118	0.0348
			Narrative substitution	0.086	0.0254
			Narrative interest	0.136	0.0401
			Narrative nonlinearity	0.138	0.0407
			Narrative memorability	0.073	0.0215
	Emotional experience	0.216	Novelty	0.152	0.0328
			Sense of discovery	0.159	0.0343
			Satisfaction	0.155	0.0335
			Pleasure sense	0.135	0.0292
			Sympathetic sense	0.129	0.0279
			Comfort	0.148	0.0320
			Sense of manipulation	0.122	0.0264
	Sensory experience	0.214	Environmental authenticity	0.151	0.0323
			Interface clarity	0.112	0.0239
			Dubbing comfort	0.096	0.0205
			Background music immersion	0.128	0.0274
			Device prompt note	0.116	0.0248
			Visual immersion	0.149	0.0319
			Information accuracy	0.132	0.0282
			Tactile perception	0.116	0.0248
	Cognitive experience	0.142	Knowledge learnability	0.326	0.0463
			The whole and part	0.368	0.0523
			System applicability	0.306	0.0435
	Interactive experience	0.133	Interactive learnability	0.354	0.0471
			Prompt clarity	0.234	0.0311
			Feedback rationality	0.187	0.0249
			Interactive interest	0.225	0.0299

There are many ways to collect user behavior data, such as questionnaires, interviews, test equipment to monitor the state of the respondents and other ways. Among them, the methods of using test equipment to monitor the interviewees and testing through the interviewees' expressions, body language and other physiological behaviors are more difficult, which not only require professional equipment, but also make it difficult to detect the audience's psychological activities. Therefore, this paper adopts the questionnaire survey method to collect audience experience data.

This paper conducts a questionnaire survey on the audience after actually experiencing the virtual display system. A total of 64 questionnaires were collected, of which 60 were valid. The user's choices in the questionnaire are assigned scores: 100 points for agreeing, 80 points for relatively agreeing, 60 points for saying it is not clear, 40 points for not quite agreeing, and 0 points for disagreeing. The results of the questionnaire were tallied and the scores were organized as shown in Table 6.

Table 6: Evaluation score

Experience factor	Total weight	Score
Narrative animality	0.0381	92.3
Narrative accuracy	0.0254	90.4
Narrative attraction	0.0419	89.2
Narrative richness	0.0271	90.3
Narrative coherence	0.0348	91.5
Narrative substitution	0.0254	92.3
Narrative interest	0.0401	90.5
Narrative nonlinearity	0.0407	83.0
Narrative memorability	0.0215	92.6
Novelty	0.0328	91.9
Sense of discovery	0.0343	90.0
Satisfaction	0.0335	93.0
Pleasure sense	0.0292	82.8
Sympathetic sense	0.0279	93.3
Comfort	0.0320	90.7
Sense of manipulation	0.0264	84.6
Environmental authenticity	0.0323	84.8
Interface clarity	0.0239	93.4
Dubbing comfort	0.0205	93.9
Background music immersion	0.0274	90.7
Device prompt note	0.0248	91.8
Visual immersion	0.0319	88.2
Information accuracy	0.0282	84.3
Tactile perception	0.0248	90.5
Knowledge learnability	0.0463	83.7
The whole and part	0.0523	93.0
System applicability	0.0435	88.9
Interactive learnability	0.0471	87.5
Prompt clarity	0.0311	84.3
Feedback rationality	0.0249	84.6
Interactive interest	0.0299	86.7

Table 7: Scores for each experience classification

Experience classification	Score
Narrative experience	89.912
Emotional experience	89.652
Sensory experience	89.306
Cognitive experience	88.714
Interactive experience	86.029

The total score is the accumulation of the scores of the corresponding experience factors multiplied by the corresponding weights, and the total score is calculated to be 89.039 according to Table 6, and the general score of 100-80 is considered to be very satisfactory to the user, 80-60 is considered to be more satisfactory to the user, and less than 60 is considered to be unsatisfactory to the user. For the five experience categories of the system evaluation, the scores were counted and the results are shown in Table 7.

The scores show that the audience is more satisfied with the overall evaluation results of the experience of the 3D virtual display of calligraphy and seal cutting works. From the statistics of the scores of each experience category, the audience's score for the narrative experience part (89.912) was slightly higher compared to the other four parts of the experience.

V. Conclusion

By constructing a generative model-based system for reconstructing and 3D virtual display of calligraphic seal cutting strokes, the digital preservation and innovative display of traditional calligraphic seal cutting works are successfully realized. The proposed method performs well in several performance indexes, reaching 0.9437, 0.9531 and 0.9542 in the three comprehensive evaluation indexes of SSIM, FM and S-measure, respectively, which are 17.2%, 10.9% and 12.4% improved compared with the traditional OTSU method, respectively. Individual test results for different stele postings show that the advantage of this method is more obvious when dealing with calligraphic seal carvings with complex backgrounds, in which the SSIM value on the Shenzhejun stele is improved from 0.6213 to 0.9042, with an improvement of 45.5%. The stroke extraction method based on the consistent point set drift algorithm effectively solves the matching difficulty problem of the traditional method in dealing with the case of large shape change, and simplifies the description and extraction process of the stroke features through the asymmetric rhombic stroke model. The autoregressive model shows good results in texture generation and significantly reduces the computational complexity compared with the traditional texture synthesis method. The 3D virtual display system obtained good user experience evaluation, with an overall satisfaction score of 89.039, among which the narrative experience scored the highest score of 89.912, indicating that the system has achieved the expected results in cultural inheritance and artistic display. The system not only provides technical support for the digital protection of calligraphic seal cutting, but also opens up a new way for the modernization and inheritance of traditional culture, which is of great significance for promoting the development of Chinese excellent traditional culture in the digital era.

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