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[1]LongHui Zhang

[2]WonjunChung

Research on the Optimization of Calligraphic Font Design Supported by Bionic Algorithm

Abstract: - In order to improve the optimization effect of calligraphy fonts, this paper firstly analyzes the correlation between calligraphy art and font design, and combines median filtering to deal with the calligraphy images to improve the clarity of fonts. Then the bionic algorithm is used to unfold the modeling of font styles to generate new calligraphy fonts. The font strokes are categorized into a sequence of skeleton features to determine the basic geometric relationship between fonts. The calligraphic font features are categorized to make the generated calligraphic image readable. Finally limit the relative change magnitude of feature vectors to construct the font design optimization process. The generated calligraphic fonts are evaluated in terms of font completeness, image quality and coverage, and it is concluded that the simulation algorithm has a font completeness of more than 95%, a peak signal-to-noise ratio between 34db-36db, and a font coverage of more than 90%, which are all better than the other two algorithms. Therefore, combining the simulation algorithm and the art of calligraphy can generate calligraphy fonts with innovative styles and moods, and the optimization effect is better, which improves the readability of calligraphy fonts and makes more and more people pay attention to the field of calligraphy.

Keywords: calligraphy font optimization; median filter; bionic algorithm; skeleton feature sequence; peak signal-to-noise ratio

1. Introduction

In today's era, calligraphy, as a traditional art form, has a profound cultural flavor and aesthetic sense [1]. And due to the development and progress of technology, calligraphy typography is gradually widely used in the field of visual communication [2]. However, traditional calligraphic font design has limitations in complexity and efficiency, which is difficult to meet today's innovative needs. Therefore, simulation algorithms and calligraphic font design are combined to generate calligraphic fonts with novel styles and rich visual elements [3]. Simulation algorithms belong to the evolutionary system of computing methods that simulate the biology of nature, which are widely used in many fields due to the unique optimization mechanism and searching ability, and gradually show more potential and value in the field of calligraphy font design [4]. The use of simulation algorithms to mimic the font form and structural layout of calligraphic fonts, so as to generate calligraphic fonts with novel mood and distinctive style, which not only retains the traditional flavor and aesthetic value of calligraphy, but also meets today's aesthetic needs [5-6].

[1] [1] School of Art and Design, Suzhou University, Suzhou, 234000,Anhui,China

[2]* Department of Visual Communication Design, Tongmyong University, Busan,Korea 48520. Email: 15956025521@163.com

This paper firstly analyzes the relationship between the art of calligraphy and font design, gets the correlation between the two, and puts forward the basic way of calligraphy subgraphy, which provides the basis for the subsequent generation of fonts. Secondly, the collected images of calligraphy works are filtered to remove the noise in the images to ensure the quality and clarity of the images. Finally, the simulation algorithm is used to model the font styles to generate new calligraphic fonts. By analyzing the three font design methods through multiple indicators, it can be concluded that the fonts generated by the simulation algorithm can meet the needs of aesthetics, and the integrity of the fonts is high. Based on the simulation algorithm, a clearer image quality can be obtained, and the calligraphic fonts have a better viewing effect.

2. Related Words

Zhou, P et al. constructed a network for generating Chinese characters based on specific calligraphic styles, and automatically generated high-quality calligraphic images through the constructed network in order to improve the problem of calligraphic transcripts which are limited by the number of characters [7]. Zhang, Y. W et al. constructed a relief dataset composed of different styles of fonts in order to preserve the calligraphy fonts for a long period of time, and formed a new dataset based on convolutional neural network, and the proposed method is able to maintain good performance at different resolutions compared to the traditional method [8]. Han, K et al. investigated how aesthetic preferences affect calligraphic styles, targeting rounded and square representations of Chinese characters, to provide a better reference for calligraphic font design decisions [9]. Lee, J. S et al. proposed the same new method of automatic font generation, where the fonts are first converted into different images, and then the text content is extracted using a style encoder to finalize the graphical design of the fonts [10]. Hassan, A. U et al. built an end-to-end network for font design optimization through interactive learning based on computer vision and computer graphics [11]. Kulahcioglu, T et al. generalized the degree of association between text and fonts, embedded the fonts using CNN and generated new fonts based on the attribute scores [12]. Wilkins, A et al. proposed text autocorrelation and Fourier transform algorithms to improve font reading generics [13]. Li, C et al. designed a font style transformation system that constructs a multilayer attention network to recognize and generate new font styles [14]. The above related researches have studied the design and optimization methods of calligraphic fonts using different methods and based on different perspectives, which provide theoretical reference for the research of this paper.

3. Calligraphic Arts and Typography

3.1 The connection between the art of calligraphy and typography

The art of calligraphy is mainly to use Chinese characters as a carrier, to express the meaning of calligraphy by means of body momentum and brushwork, etc., to emphasize the structure and lines of abstract words, and to show the beauty of sinews and bones from the works of calligraphy, so that the viewers can discover the meaning of calligraphy from the works [15].

In the art of calligraphy, the brushwork is in the first place. The brushwork of calligraphy refers to the method of regularity of different strokes in a calligraphic work. The brushwork comes first, then the chapter and the ink.

Brushwork makes the dots and lines of a script have changes and strength, more regularity and regularity. In the art of calligraphy, chapter method is also an indispensable part. Chapter law is mainly in the layout of the work to deal with the relationship between words and words and lines and lines, so that the overall work has a more echoing effect, so that the calligraphy work has the beauty of the mood. The color of ink in calligraphy can not be haphazard, there needs to be a certain order and rules. Calligraphy ink color is generally divided into two kinds, one is the ink color combination of the dot painting structure, need to pay attention to the layering effect of the ink color, reflecting the depth of expression of calligraphy. Secondly, when the background color is divided, it is necessary to count white as black. The junction in calligraphy refers to the inter-frame structure when the font is written, the arrangement and situation of the word point see, so that it produces the effect of reality and falsehood in space. Typeface design is mainly in accordance with the visual law of the font layout, set the structure and size of the font, so that the font has a strong visual attraction, so as to convey the deep-seated flavor of the text. Typography and human beings have always been closely related to the requirements of the text in the transmission of meaning at the same time with a sense of beauty and design personality.

Figure 1 shows the correlation between calligraphy art and font design as follows:

(1) There are the same cultural locations are the same, embodied in different words with different aesthetics and characteristics, which provide the basis for the creation of calligraphy art and font design. Calligraphy art contains cultural content, and font design needs to be based on traditional culture to create new ideas, not confined to a fixed form. The two output locations are the same, so they have the same aesthetic and form.

(2) The formation of the art of calligraphy has been closely related to the font design, the font after the font design, with a new writing method and layout, providing a new writing style for calligraphy. At the same time, the art of calligraphy is also a form of writing font design, the more artistic the font design, the more it can become a source of calligraphy design.

(3) The art of calligraphy has always been the art of lines, in which the vividness, changeability and figurativeness of lines provide inspiration for font design. The creativity of font design mostly borrows the expression means of calligraphy art, which makes the font become refreshing and eye-catching. Plain and simple, bright and vivid and dangerous undulating line style for the font design of the pen point line to provide a constant stream of creative methods, so a good calligraphy art is the inspiration of the font design.

(4) No matter how the writing carriers of calligraphy art change, the specifications between words and the combination of word shapes have always contained the corresponding rules. In visual communication, points, lines and surfaces are the main visual forms, so font design and calligraphy have similar aesthetic criteria, not only to let the audience understand the meaning of the text, but also to let the audience view the art of the font, to achieve the best effect of information dissemination [16].

(5) The art of calligraphy focuses on the expression of national culture and personality, so the development of typeface design also pays more attention to the expression of national culture, so as to find the cultural

positioning and cultural home, and to obtain a sense of national identity. The essence of calligraphy art and font design is the role of human consciousness in the material, is the expression of human emotion, with its own national feelings and culture, so the calligraphy art and font design both have the support of the national culture, and mutually contribute to the development of the long term.

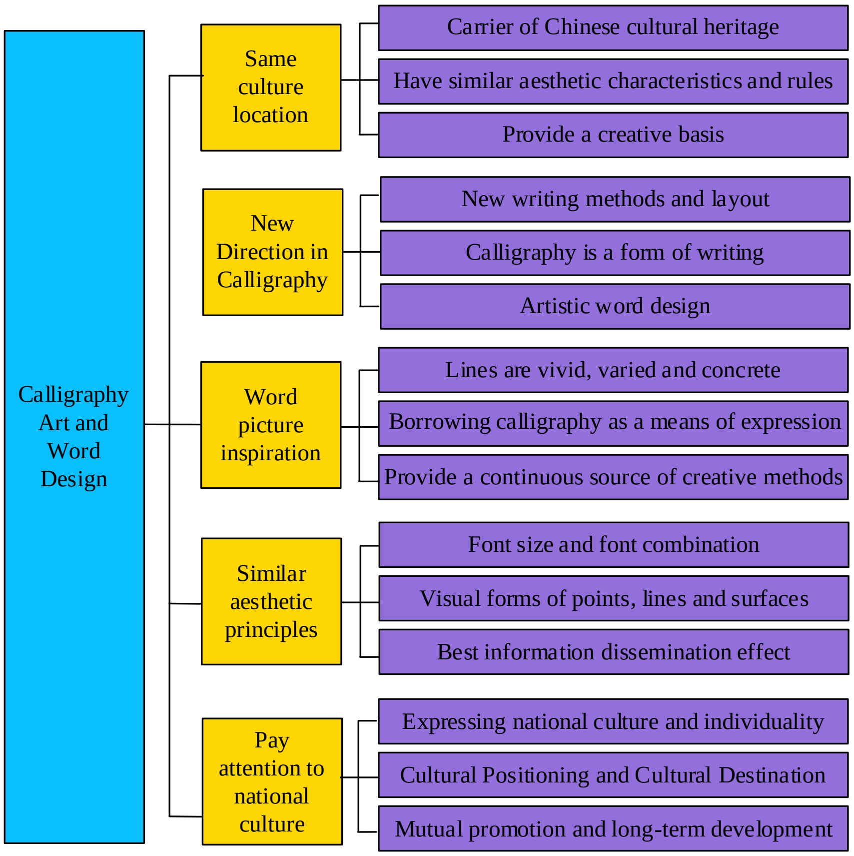

Figure 1 The relationship between calligraphy art and character design

3.2 Calligraphic Subdivision

Calligraphy sub-division is an important part of calligraphy art design, refers to the expression of the characteristics of the theme and mood, the calligraphy work is divided into different visual areas, and different areas are set up to present different expression effects. There are usually the following kinds of calligraphic divisions:

(1) white space is relative to the black lines left on the paper, used to assist the lines, thus forming a complex phase to phase convection. This convection is often such that if the black color changes slightly, the white color changes with it. Before a piece of white paper is used as a calligraphic material, it appears visually flat. Once it is used as a calligraphic material, it needs to be cut into a certain format, gradually entering the realm of art. Therefore, in the layout design, in order to be able to highlight the main body of information, need to retain the appropriate proportion and blank space in the layout, used to enhance the readability of the layout. The layout of the white space needs to consider the location and direction of the main body of information, taking into account the layout of the air and extension, the formation of three-dimensional space, echoing each other.

(2) Juxtaposition is generally a common combination of images and text between the way, one is up and down the structure, located below the image, which is more common is centered alignment, between the image and text to form the appropriate proportionality and primary and secondary relationships. If there is more text, can be arranged into two or more lines, but several lines of text between the need to differentiate according to the focus of the content, in font and thickness to make appropriate adjustments. Graphics can also be used left or right alignment, as a way to form a new visual effect. Second, left and right structure, the image and text left and right layout, graphics arranged in the text of the left and right sides, read the text first in the picture, or first look at the picture and then look at the text, easy to view and read, but also more convenient to read the order of the logo can be adjusted according to the logo design of the idea of the size of the relationship between the icon and the text, to coordinate the relationship between the icon and the text of the primary and secondary. If the text content is too much, you need to arrange several lines of text in an orderly manner, and arrange the overly long content in several rows.

(3) Diagonal looking at each other means that the image and text are located in the diagonal position of the composition, this method of communication is different from the traditional symmetrical position, which will allow the logo visual framework of the white space in the expansion of the area, so that the calligraphic works have a more contemporary sense. Because breaking the traditional structure of the graphic and text collocation, can be more flexible placement of graphic shapes and text arrangement. However, it should be noted that the diagonal looking graphic combination needs to control the balance of text and graphics in the trend, so that the text is balanced in the asymmetry. In the internal details of the text and graphics to achieve, the internal structure is compact, the external to the external expansion of tension.

4. Calligraphy Image Processing

Since the collected images of calligraphy works may be distorted, it is necessary to process the images to make them clearer for subsequent font design [17].

Adaptive median filtering is used to process the image, which is divided into three aspects: noise detection of the image area, determination of the filter window size according to the detected noise, and filter measurement of the noise points. Noise detection is a key step in image processing, which provides the basis for the subsequent classification of image pixels to better ensure the quality of the image.

The image of size $M \times N$ is divided into S sub-blocks and the k $(k = 0, 1, \cdots, S-1)$ th sub-block is denoted by B_k. The pixel point (i, j) that needs to be detected within the sub-block has a grayscale value of $f(i, j)$. The point is used as the center to generate a detection window of size 3 × 3, and the grayscale value in the window can be obtained as:

$$A_{i,j} = \left\{ f(i+s, j+t) \middle| (i, j) \in B_k, s, t \in [-1, 1] \right\} \tag{1}$$

In the formula, the minimum and maximum gray values of set $A_{i,j}$ are $Min(i,j)$ and $Max(i,j)$, respectively, and the gray values in set $A_{i,j}$ and the maximum and minimum are not equal to form set $C_{i,j}$, and find the average value of all gray values in set $C_{i,j}$. $T(i,j)$, if the difference between $f(i,j)$ and $T(i,j)$ is larger than the threshold value of T_d, and the values of $f(i,j)$, $Max(i,j)$, and $Min(i,j)$ are equal, (i,j) is a noise point, and $y_{i,j}=1$ is used as a marker, and vice versa, (i,j) is a non-noise point, and $y_{i,j}=0$ is used as a marker, the specific equation as follows:

$$f(i,j)=Max(i,j)\subseteq\bigcup f(i,j)=Min(i,j)\bigcap\left(\left|f(i,j)-T(i,j)\right|\geq T_d\right) \tag{2}$$

In the formula, the threshold value T_d has a greater impact on noise detection, the size of the degree and the size of the noise is related to the noise size, the noise interference is larger, the value of T_d is larger, the noise is smaller, and the value of T_d is smaller.

In sub-block B_k, the size of the filter window is decided according to the noise size p_k of the sub-block, and p_k is the ratio of the number of noise points and the total number of pixels to satisfy $y_{i,j}=1$. When p_k is small, a filter window with a small size is selected to remove the noise, and when p_k is large, a filter window with a large size is selected to remove the noise, as shown in the following equation:

$$l_k=\begin{cases}0, p_k\leq w_1\\3, w_1\leq p_k\leq w_2\\5, w_2<p_k\leq w_3\\7, p_k>w_3\end{cases} \tag{3}$$

In the formula, when the noise interference p_k is small, the window length is $l_k=0$, and no processing is unfolded on the sub-block B_k, and when p_k is large, the processing is unfolded on B_k using the window of length l_k, and w_1, w_2, w_3 represents the constant, which meets the condition $0<w_1<w_2<w_3<1$.

After completing the noise detection, the pixels in the image will be divided into non-noise and noise parts, retaining the gray value of non-noise, and filtering the processing of noise obstetrics.

The processing of sub-block B_k in the calligraphy image is unfolded with a filter window of size l_k of $(2L+1)\times(2L+1)$ and noise contaminated pixels (m,n) with a gray value of $f(m,n)$. The four directions within the window, 0, 45, 90 and 135, are selected as the filtering directions to protect the directional details of the image. This results in sub-windows $W_0(m,n), W_1(m,n), W_2(m,n)$ and $W_3(m,n)$, specifically:

$$\begin{aligned} W_0(m,n) &= \{ f(m,n+l), -L \le l \le L \}; \\ W_1(m,n) &= \{ f(m+l,n-l), -L \le l \le L \}; \\ W_2(m,n) &= \{ f(m+l,n), -L \le l \le L \}; \\ W_3(m,n) &= \{ f(m+l,n+l), -L \le l \le L \}. \end{aligned} \tag{4}$$

Let $Z_0(m,n), Z_1(m,n), Z_2(m,n)$ and $Z_3(m,n)$ represent the median pixel gray values of the four sub-windows as follows:

$$Z_k(m,n) = med\left[W_k(m,n)\right], k = 0,1,2,3 \tag{5}$$

where $med[\circ]$ represents the median filtering, and the filtering results of the above sub-windows are weighted and summed to obtain the filtered gray value of the pixel point contaminated by noise as:

$$g(m,n) = \sum_{k=0}^{3} c_k Z_k(m,n) \tag{6}$$

where $c_k\ (k = 0,1,2,3)$ represents the weighting factor, the magnitude of which is determined according to the median filtering, as:

$$c_k = \frac{Z_k(m,n)}{\sum_{i=0}^{3} Z_i(m,n)} \tag{7}$$

According to the above process to complete the denoising of the image of the calligraphy work, so that the image is clearer and easier for the subsequent design of the calligraphy font [18].

5. Optimized modeling of fonts supported by simulation algorithms

5.1 Calligraphic style

In calligraphy fonts, the Chinese character styles of calligraphy can generally be divided into four levels; compound strokes, radicals and bias, basic strokes and single characters. The basic strokes are mainly composed of horizontal, vertical, apostrophe, press and dot, while the other three levels are combinations of information from the previous layer.

A basic stroke is generally divided into multiple sequences of skeletal features, each of which has four components representing the horizontal and vertical coordinates of the skeleton, as well as the width and type of the skeleton. The envelope box is used to represent the structure of the strokes in a calligraphic typeface design and to determine the basic geometric relationships between fonts. The envelope box is represented by

$box = (height, width, center, angle)$, where $width$ and $height$ represent width and height, $center$ represents the center, and $angle$ represents the angle.

5.2 Calligraphic font modeling and optimization

5.2.1 Classification of calligraphic fonts and modeling process

Based on the collected or user-input images of calligraphic fonts, the simulation algorithm is utilized to control the parameters to generate new calligraphic fonts. In the generation of calligraphic fonts, the skeleton structure of calligraphic fonts needs to be searched and matched, and the searching and matching of skeleton structure is a fuzzy classification problem, which needs to consider factors such as translation invariance and rotation invariance. The support vector machine method is used to extract and classify the features in the calligraphic fonts to enhance the readability of the font design.

The main idea of the support vector machine classification method is to transform the $k(k>2)$-class problem into a k -division problem, and the i -division problem is to divide the i th class and the rest of the classes into each other, and let the decision function for dividing the i th class and the rest of the classes be as follows:

$$D_i(x) = w_i^t x + b_i \tag{8}$$

In the formula, $D_i(x)=0$ represents the optimal classification to distinguish between category i and other categories, the support vector belonging to category i , satisfies $D_i(x)=1$, and the support vector of other categories satisfies $D_i(x)=-1$. For the samples to be categorized in the calligraphic works x , they are classified into category i when condition $D_i(x)>0$ is satisfied, and they are not classified when there are more than one category to satisfy the condition. The relevant decision function to distinguish between i and j is as follows:

$$D_{i,j}(x) = w_{ij}^t + b_{ij} \tag{9}$$

where $D_{i,j}(x) = -D_{jx}(x)$, w^t represent the weight vectors and for sample x the new class i decision function is as follows:

$$D_i(x) = \sum_{j=i, j\neq i}^{n} D_{i,j}(x) \tag{10}$$

Sample x to be classified in the calligraphy work is classified into the i nd class under the condition of $i = \arg\max D_i(x)\, i = 1,2,\cdots,n$, but there will still be a situation where x it cannot be classified, so it is necessary to introduce a fuzzy affiliation function for the classification surface $D_{ij}(x)=0$ fuzzy degree of affiliation function $m_{ij}(x)$ in the direction of perpendicular to the hyperplane is given in the following equation:

$$m_{ij}(x)=\begin{cases}1 & D_{ij}(x)>1\\ D_{ij}(x) & Other\end{cases} \tag{11}$$

Class i fuzzy affiliation function is as follows:

$$m_i(x)=\min D_{ij}(x) \quad (j=1,2,\cdots,n,\ j\neq 1) \tag{12}$$

The condition for classifying the sample x to be classified to class i in the calligraphy work is $i=\arg\max m_i(x)(i=1,\cdots,n)$. Using the fuzzy affiliation function, the problem of searching and matching the skeleton structure in the calligraphy work is accomplished to make the generated image more readable.

5.2.2 Optimizing processes

After obtaining the accurate skeleton structure of the calligraphy work image according to the above process, a new font image can be generated by the information of the skeleton structure and the pixel points in the image.The main idea of the simulation algorithm is divided into the analogical stage and the evolutionary stage [19].

Firstly, in m image of different styles of the same calligraphic characters, the skeleton structure Sk_i of the characters in the calligraphic works is taken as the source of evolution, and the set of key points P_i on the skeleton structure is obtained by interpolation, the other $(m-1)$ calligraphic font images are expanded and sorted according to the shape similarity feature, and using the similarity of the skeleton structure, the skeleton points of the other $(m-1)$ calligraphic font images are classified into the corresponding set of skeleton key points. Then, using the results of the first stage, the skeleton structure triad (x,y,r), which is the evolution source, is shifted under the action of the skeleton structure similar keypoints of the corresponding other $(m-1)$ calligraphic font images, and the effect of the shifting is related to the similarity of the skeleton structure with the skeleton structure of the evolution source, and is also proportional to the similarity of the point with the keypoints of the evolution source that is being acted upon. The number and coherence of the envelope boxes of the new skeleton structure should be basically the same as that of the skeleton structure of the evolutionary source, and the difference of the coherence of the envelope boxes should be within a threshold, and the properties of the strokes should not be destroyed in the action, thus constituting a new font image.

In the generation and evolution process of calligraphic font works there is m calligraphy skeleton image, each skeleton image has n sequences of discrete feature points, where $x_{i,j}, y_{i,j}, r_{i,j}$ and $w_{i,j}$ represent the coordinates, stroke widths, and weight values of the hashed feature points, respectively, and the set of key points before the evolution of calligraphic font works is:

$$P_{ij} = \left(x_{ij}, y_{i,j}, r_{i,j}, w_{i,j}\right)\left(i = 1, 2, \cdots, m; j = 1, 2, \cdots, n\right) \tag{13}$$

The set of key points of the new image skeleton obtained after evolution is:

$$\begin{cases} \hat{P}_{ij} = \left(\hat{x}_{ij}, \hat{y}_{i,j}, \hat{r}_{i,j}, \hat{w}_{i,j}\right)\left(i = 1, 2, \cdots, m; j = 1, 2, \cdots, n\right) \\ \hat{P}_{i,j} = \mathrm{Pr}\,ob \leftarrow P_{i,j} \end{cases} \tag{14}$$

Where $\mathrm{Pr}\,ob$ represents the normal distribution function of the skeleton feature points of the calligraphy image, and $\leftarrow$ represents the set of feature point sequences of the normal distribution function acting on vector P_{ij}.

By adjusting the variance and mean, we can obtain the evolution results with different degree of similarity with the original sample image, and generate the new calligraphy font image. In order to ensure that the evolution results satisfy the basic font structure constraints, the relative change of the above feature vectors is limited to not more than three times the mean squared deviation, beyond which the truncation principle needs to be applied to ensure the regularity of the structure. For the change of the sample mean, the multiplicity is set in the range of [0.8,1.2], and the result is better.

The main flow of the simulation algorithm is as follows:

(1)For the $m\left(m > 2\right)$ collected images of the same calligraphy font with different styles, set each of them to have equal weights in the evolution.

(2) According to the shape similarity feature vector, each calligraphy font image is sorted in m rounds as a criterion, and the one with the criterion image sorted as [m/2] is selected as the source of evolution.

(3) Set the mean and variance of normal distribution to determine the evolution weight parameters of various basic strokes in calligraphic fonts.

(4) Obtain the skeleton structure from the evolution source image, and obtain i key feature point by spline interpolation method.

(5) Obtain the skeleton structure of $m-1$ calligraphy font images, divide the skeleton points into i classes according to the similarity with the key feature points of the evolution source, and assign different weights according to the similarity.

(6) According to the values of the triad of points with different weights in the same class, the evolution of the

$\{x, y, r, w\}$ values of the key points is carried out, and the new skeleton structure of the calligraphic font features is obtained.

(7) Check the constraints of the new skeleton structure and remove the unqualified results.

(8) Reconstruct the calligraphic font skeleton to generate a new calligraphic font image.

For the evolution results that do not meet the structural constraints can not be completely removed, but the variance should be controlled within a certain threshold. According to the above process to complete the design optimization of the calligraphy font image, to generate a new font image, enhance the visual effect and readability of the font image.

6. Calligraphy font design optimization effect analysis

6.1 Font Integrity Testing

Font integrity test is an important index to evaluate the optimization of font design, which is used to assess whether the font file is complete and the contained characters can be displayed normally in the calligraphy font design. In general, the higher the font integrity, the proof that the individual strokes, radicals and structures in the calligraphy font design are not missing or damaged, and the lower the font integrity, the proof that the strokes in the calligraphy font are damaged, and the font can not be displayed normally, with poor integrity and poor readability. Therefore, it is necessary to carry out the font integrity test on the calligraphy font design of the simulation algorithm, the deep learning algorithm and the skeleton optimization technology, and the results of the completeness test are shown in Table 1.

The font completeness of the calligraphy font design of the simulation algorithm is high, above 95%, and the structure of the fonts in the calligraphy font design is reasonable, the strokes are clear, there is no broken strokes and blurred phenomenon, and there is no result of font damage and lack of fonts, which proves that the generated image effect is better. Deep learning and skeleton optimization algorithms have a lower degree of completeness, at about 85% and 75%, there will be unreasonable structure, damaged or missing fonts, the generated calligraphy fonts have more serious broken strokes, fuzzy fonts, which affects the viewing effect, and the algorithm is less effective.

Table 1 Font integrity analysis

Font area	Analysis and description	Simulation algorithm completeness/%	Completeness of deep learning algorithm/%	Skeleton optimization completeness/%
Basic strokes	The strokes are clear, coherent, and without broken strokes	93%	83%	75%
Stroke order	The strokes are correct	95%	83%	73%

	and meet the standards			
Structural proportions	The font shape is reasonable and the proportions are coordinated	95%	85%	75%
White space	The blank space is reasonable, not too large or too small	96%	83%	75%
Font style	The style is distinctive and meets the requirements	95%	84%	74%

6.2 Image Quality Testing

Image quality test is an important index to measure the optimization of calligraphy font design by algorithms, which is mainly used to reflect the clarity of the calligraphy font design and determine whether the calligraphy font has a distortion condition after designing and generating. The simulation algorithm, the skeleton optimization and the depth of the student's calligraphy font design to start the image quality test, Figure 2 shows the three algorithms of the image quality test results. It can be seen that the calligraphy fonts generated by the simulation algorithm have high clarity due to the filtering processing algorithm to remove the noise in the image, and the peak signal-to-noise ratio is between 34db-36db without distortion. The image distortion of the calligraphy font design of the deep learning and skeleton optimization algorithms is more serious, and the peak signal-to-noise ratios of the two algorithms are below 24db due to the fact that the noise in the image is not removed in advance. This results in poorer clarity of the generated calligraphy fonts, making it difficult to identify the font style in the image, and the calligraphy font design fails to meet the optimization criteria.

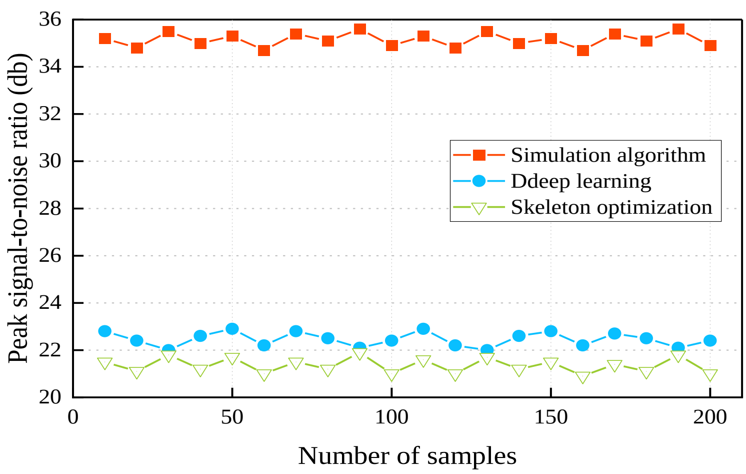

Figure 2 Image quality comparison results

6.3 Calligraphic font coverage

The percentage of different calligraphic styles and styles in generating and optimizing font designs for live selection is measured by the algorithm using the calligraphic font coverage. The higher the calligraphic font coverage, the more calligraphic styles the algorithm collects, the more novel and valuable the generated font styles are. Figure 3 shows the font coverage rate of the three algorithms, in the case of the number of samples 0-500, the simulation algorithm has a higher coverage rate of more than 90%, covering most of the calligraphy font styles and styles, which can generate calligraphy fonts with novel styles and rich visual elements, and the optimization effect of calligraphy font design is better. The coverage rate of deep learning and skeleton optimization algorithms is lower at about 75% and 60%, which is difficult to cover most of the calligraphic styles and styles, and the generated calligraphic fonts are not innovative enough, with fewer visual elements and less ornamental, so it is difficult to design better calligraphic fonts, and the optimization effect is not ideal.

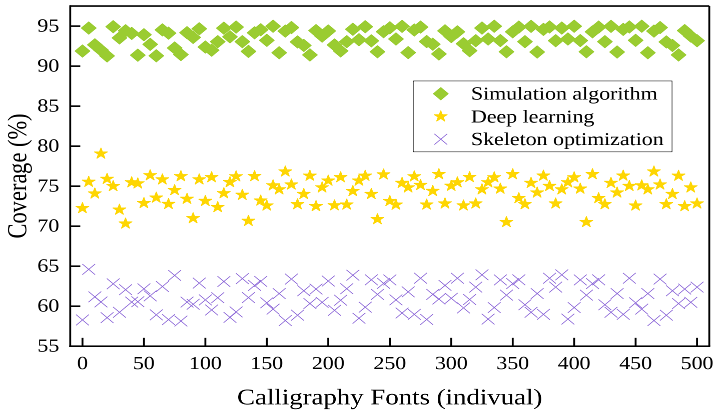

Figure 3 Word graph coverage of three algorithms

6.4 Typography Optimization Efficiency

In order to verify the font design optimization efficiency supported by the bionic algorithm, the generation time and resource consumption are then compared with the deep learning and skeleton optimization algorithms, and the results of the comparison of the font design optimization efficiency are shown in Table 2.The bionic algorithm consumes the shortest amount of time under the number of fonts from 100 to 500, which is between 10.2s-14.2s, and the other two algorithms are all above 20s. In terms of memory usage, the megabyte consumption of the bionic algorithm is also the lowest, with low fluctuation, gradually increasing to 95.1MB, and in the case of 500 fonts, the memory usage of the deep learning and skeleton optimization algorithms are 260.9MB and 250.6MB respectively. it can be seen that the optimization of the calligraphy fonts based on bionic algorithms designed in this paper is the most efficient, especially in terms of time and memory usage, which plays a better role in optimizing the design.

Table 2 Comparison of font design optimization efficiency

Number of fonts	Time/s			Memory usage/MB		
	Bionic algorithm	Deep learning	Skeleton optimization	Bionic algorithm	Deep learning	Skeleton optimization
100	10.2	22.1	25.4	90.1	220.2	231.5

200	11.3	23.4	26.8	92.4	230.6	242.4
300	12.5	24.0	27.1	93.5	240.5	246.7
400	13.4	24.2	27.5	94.5	245.8	249.6
500	14.2	25.6	28.6	95.1	260.9	250.6

7. Conclusion

Based on the characteristics and correlation between the art of calligraphy and font design, this paper studies the characteristics of the calligraphy sub-images to pave the way for the subsequent generation of calligraphic fonts that meet today's aesthetics. Then the median filtering method is utilized to remove the noise of the calligraphy image so as to avoid distortion of the image. Finally, the simulation algorithm is utilized to establish the style of calligraphy fonts and complete the generation of calligraphy fonts. In order to analyze the effect of calligraphy font design, the analysis of calligraphy font design is completed from the three indexes of font integrity, image quality and coverage, which proves that the simulation algorithm generates better calligraphy fonts, with higher font integrity, which can accurately show the form of fonts and conform to today's style of fonts, at more than 95%, whereas the other two algorithms have poorer integrity at about 83% and 75%, which makes it difficult to accurately represent the complete fonts. And the coverage of the emulation algorithm is higher, above 90%, covering most of the calligraphic styles and styles, as a way to be able to generate rich calligraphic styles. The shortest time consumed for the optimization of digital font design supported by the bionic algorithm is between 10.2s-14.2s, which proves that the proposed study has a good optimization efficiency. In the future, the application of bionic algorithms in calligraphic font design can be further studied and explored, and combined with other fields to provide new possibilities and directions for the innovation and inheritance of traditional culture.

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