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Research on the Digital Development of Calligraphic Art under the Perspective of Semiotics

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SUMMARY: *Based on semiotics, this paper systematically researches the preprocessing, structural analysis and artistic information extraction methods of calligraphic characters for the key problems in the digitization of calligraphic art. Combining the writing rules and the definition of skeleton diagram to realize the text structure analysis, and put forward the algorithm of calligraphic art information extraction based on partitioned bootstrap filtering. Carrying out experiments on digitization of calligraphic art and introducing different mainstream methods to compare and verify their effectiveness. In the task of burr detection, this paper's algorithm has the best overall performance, with an accuracy of 99.27%, which is significantly higher than that of the threshold method (97.32%), the significance-ordered pruning method (80.13%) and the automatic pruning method (94.92%). In the skeleton extraction task, this paper's algorithm strokes the skeleton with an accuracy of 99.04% and a processing speed of 8.93 characters/second, striking a balance between accuracy and efficiency. In the quantitative comparison experiment this paper algorithm still has obvious improvement on the index, F1, IoU is 0.7018, 0.5264 respectively.*

KEYWORDS: *calligraphic art; semiotics; digitization; text structure analysis; partitioned bootstrap filtering; skeleton extraction*

1 Introduction

As a unique cultural symbol of the Chinese nation, the art of calligraphy has a long history and has evolved over thousands of years, condensing the wisdom and emotions of the children of China. From the oracle bone inscriptions of the Yin and Shang Dynasties, to the gold and seal scripts of the Zhou and Qin Dynasties, to the official scripts of the Han Dynasty, the cursive scripts of the Wei and Jin Dynasties, and the regular scripts of the Tang and Song Dynasties, the art of calligraphy not only records the historical changes of the Chinese nation, but also contains rich philosophical thoughts, aesthetic concepts, and cultural spirits [1-3]. In traditional societies, calligraphy relies on pen and paper, and is passed down from generation to generation through the teaching of masters and disciples, the continuation of the family, and the exchange and mutual appreciation between literati and artists [4]. However, with the rapid development of information technology, the advent of the digital era has completely changed people's way of life and the mode of cultural dissemination, and the environment for the survival and development of the art of calligraphy has undergone a radical change [5-7]. On the one hand,

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the wide application of electronic writing tools has gradually marginalized the traditional brush writing, and the inheritance of the art of calligraphy is facing a severe test [8]. On the other hand, digital technology provides unprecedented opportunities and broad space for the protection, dissemination and innovation of calligraphy art [9].

In the era of digitization, electronic input devices such as keyboards and touch screens have become the main tools for people's daily writing, and the writing of Chinese characters has gradually transformed from traditional handwriting to machine input. Literature [10] attempts to construct a knowledge base for the art of Chinese calligraphy using advanced techniques such as graph databases and fuzzy logic; this knowledge base, which focuses on the relationships between characters and contains interactive, game-like exercises, will serve as the basis for teaching the art of calligraphy in the digital age. Literature [11] developed fifteen design guidelines for the art of digital calligraphy through a systematic literature review, in which finger size, contact area, motor skills, tactile perception, and input location relate to the characteristics of human fingers, and orientation, structure, font style, complexity, and semantics relate to the characteristics of Chinese characters. Literature [12] suggests that Natural Language Processing (NLP) is the key technology for digital calligraphy art, and the technology plays an important role in character checking, character error correction pairs, and this dramatic change in writing style has gradually weakened the perception of the thickness, length, curvature, and straightness of the Chinese characters' strokes, as well as the rhythm and rhyme of writing. The aesthetic elements emphasized in the art of calligraphy, such as brushwork, ink, structure and chapter, need to be deeply understood and felt through personal writing experience, while the convenience of digital calligraphy art makes it difficult for people to quietly taste the rhythm and mood of calligraphy, resulting in the public's aesthetic perception of the art of calligraphy becoming indirect and abstract [13, 14].

The development of digital technology for the dissemination and communication of the art of calligraphy, has brought a revolutionary breakthrough. The popularization of the Internet has broken the limitations of time and space, and calligraphic works can be rapidly disseminated around the globe in the form of digital images and videos [15]. Literature [16] explores the application of calligraphy art in digital media by using big data technology, focusing on the fact that with the help of the Internet and the big data analysis platform, the collection and visualization of data on calligraphy art can be realized, which indirectly improves the access rate of calligraphy art. Literature [17] believes that under the background of informationization, it is necessary to accelerate the construction of digital video courses of the art of calligraphy, as well as the construction of professional learning platforms of digital network new media, and it is also necessary to strengthen the interactive experience of digital calligraphy, as well as the derivation and expansion of the culture of calligraphy, so as to truly realize the digital dissemination of the art of calligraphy. Literature [18] that the dissemination and development of traditional calligraphy art and culture, the need for continuous innovation to adapt to modern needs, the use of new media technology can effectively show the spiritual connotation of the work of art itself, so as to realize the effective dissemination and inheritance of the art of calligraphy, and promote the excellent traditional calligraphy art and culture to the international community. Literature [19], on the basis of empathic communication theory, proposes an innovative framework for the art of calligraphy, aiming to utilize multimedia digital technology to display its dynamic charm, as well as to promote interactive experiences and cross-cultural educational activities, thereby realizing the dual goals of cultural identity and global communication by triggering emotional resonance.

In this paper, we first apply the methods of denoising, smoothing and normalization to preprocess the calligraphic characters. Mutual positional relations are introduced to the components to obtain the font structure information of the text components. The traversal order of each subgraph represented by the components is extracted to realize the text structure analysis. The algorithm for extracting calligraphic art information based on partitioned bootstrap filtering is designed to extract the basic information of the calligraphic characters in the calligraphic posting image using the K-nearest neighbor keying algorithm. Different sizes of filtering windows are used for the filtering process, and the artistic information extraction results are obtained by pixel-level image fusion technology. Select examples to start the analysis and adopt the proposed method for calligraphy character extraction. Design performance tests and comparison experiments to evaluate the performance level of the proposed method.

2 Digitally driven algorithms for the analysis of calligraphic art

Calligraphy, as the core carrier of Chinese excellent traditional culture, its digital protection and artistic feature extraction is an important topic of cultural heritage and technological innovation. Currently, traditional calligraphy images are often affected by noise interference, complex backgrounds and irrelevant elements such as seals, resulting in insufficient accuracy of key information extraction, which makes it difficult to meet the needs of archiving, restoration and style analysis. Existing methods still have technical bottlenecks in the retention of ink features, edge detail processing and multi-type interference removal. In this paper, we focus on the digital development of calligraphy under the perspective of semiotics, and propose an algorithmic system focusing on the key aspects of calligraphy word preprocessing, structure analysis and artistic information extraction.

2.1 Preprocessing of Calligraphy

2.1.1 Initial denoising

Images of original calligraphic work pages scanned from books contain a lot of noise. These noises include red seals stamped by calligraphers and collectors, moldy spots left by natural weathering and corrosion, etc. In addition to this, the pages of calligraphy books usually contain other information such as page numbers and names of works in addition to the area of the calligraphic work. These information effectively indicate some metadata information of the calligraphic works, but they are useless for studying the calligraphic characters themselves, so they need to be removed in advance.

The information such as page number, work name, etc. on the pages of the book can be removed very easily by selecting the valid range as they are not within the valid range of the calligraphic work. In calligraphy character books, the tablet is white on a black background, most of the book posters are black on a gray background or black on an earthy yellow background, and the background color of the area where the page number, name of the work, and other information is printed is white. For inscriptions, just count the number of connected black dots within the boundary, if it is greater than the given Kan value of 500 pixel points (under the scanning accuracy of 300~600dpi), it is considered to be a valid range, otherwise, it belongs to the page, the author and other information to be excluded. For gray background or earthy yellow background of the book post can also be dealt with in a similar way, to find the gray or earthy yellow area, is the content of the book post. For a small number of white background black calligraphy, you can also seek to scan to get the horizontal and vertical color histogram of the page, from the histogram to get the exact scope of the calligraphy.

What is more difficult is to remove the noise mixed with the calligraphic characters, such as seals. Ancient seals are usually red, while the ink color is black and the paper is white or yellow. Although the color of seals can be gray and black due to oxidation over time, they are still quite different from the ink and paper colors. This is a feature that can be exploited. Assuming that the RGB value of the color of a pixel point p is ($p.red$, $p.green$, $p.blue$), the formula for its grayscale value is:

$$p.grey = 0.11 \times p.red + 0.59 \times p.green + 0.30 \times p.blue \tag{1}$$

A pixel point is considered to be a stamp when the red component makes up more than a certain percentage of the grayscale value. The above equation can be expressed by conversion as:

$$p.red > \lambda_r \times (0.59 \times r.green + 0.11 \times r.blue) \tag{2}$$

Seals are only found in book posts where the color of the paper is usually white or yellow. After years of weathering, the paper color usually changes to light gray and yellow-black. The mixture of these colors is compared, and when the red component accounts for more than 11~15% in the gray value, the pixel point is a seal point.

In this way, pixel points that satisfy equation (2) are removed as stamp points.

2.1.2 Further denoising and smoothing

As the images of the original calligraphic works obtained by scanning or reprinting the historical calligraphic works contain a lot of noise, most of these noises are confined to one tiny area, such as speckles, scratches, and small voids in the font. In the calligraphy post, these noises are generally randomly and uniformly distributed, but in the tablet post, most of these noises are distributed on the contour lines of the calligraphic characters. Therefore, when further denoising and smoothing, in addition to removing the noise on the tiny regions as much as possible, removing the noise on the contour lines of the calligraphic characters becomes one of the focuses.

Most of the noise in the tiny areas can be removed using mathematical morphology. Spots and scratches in them are removed using open operations and small voids in the font are filled using closed operations.

Books are digitized in CADAL at a scanning resolution of 600 dpi, and the length and width of the scanned calligraphic characters are usually 400 pixels or more. In order to remove the noise from the outline of the calligraphic characters more efficiently, the maximum size of the noise block is defined as 3 × 3 pixel points. One of the matrices used for removing burrs is shown in Fig. 1(a), where 1 denotes black and 0 denotes white, and at least one pixel point in the region labeled X must be black. A matrix used for filling voids is shown in Figure 1(b), where again 1 means black and 0 means white, but at least one point in the region labeled Y must be white. The matrix shown in Fig. 1 has the burrs that can be removed and the cavities that can be filled on the bottom, and the matrices used for the other three directions can be obtained by turning these two matrices to the left, to the right, and flipping them.

1	1	1	1	1	1	1
1	1	1	1	1	1	1
0	0	X	X	X	0	0
0	0	X	X	X	0	0
0	0	X	X	X	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0

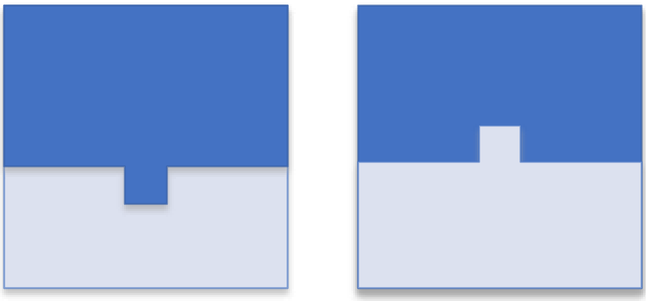
(a) Matrix for deburring

1	1	1	1	1	1	1
1	1	1	1	1	1	1
1	1	Y	Y	Y	1	1
1	1	Y	Y	Y	1	1
1	1	Y	Y	Y	1	1
0	0	0	0	0	0	0
0	0	0	0	0	0	0

(b) Matrix for filling cavities

Figure 1: The matrix used for further noise reduction

A typical burr-type noise and cavity-type noise are shown in Fig. 2 (a~b), respectively. The removal method is simply to set all the pixel point values at the X position in the region matching the above matrix to 0 and all the pixel point values at the Y position to 1. This smoothing process can be carried out cyclically. In order to prevent over-smoothing from blurring the calligraphic character image, the maximum number of smoothing times is set to 3.



(a) Burr-type noise (b) Cavity-type noise

Figure 2: Two different types of noise on the edge

2.1.3 Normalization of Calligraphic Characters

When searching and recognizing calligraphic characters, the similarity between calligraphic characters is compared. But different sizes of calligraphic characters cannot be compared directly, they need to be scaled to the same size. This is the process of normalization.

Common normalization methods for handwritten characters can be divided into two categories: linear normalization and nonlinear normalization. Linear normalization is simpler to compute, but it may affect the original topology of the characters when the scaling ratio is larger; nonlinear normalization is more complicated, but it can fully retain the original stroke structure ratio of the calligraphic characters.

Nonlinear normalization is usually based on density equalization. The common expression is as follows:

$$m = \sum_{k=1}^{i} H(k) \times \frac{M}{\sum_{k=1}^{I} H(k)} \tag{3}$$

$$n = \sum_{k=1}^{j} V(k) \times \frac{N}{\sum_{k=1}^{J} V(k)} \tag{4}$$

where $H(k)$ and $V(k)$ are the stroke densities in the horizontal and vertical directions, $i = 1, 2, \ldots, I$, $j = 1, 2, \ldots, J, m = 1, 2, \ldots, M, n = 1, 2, \ldots, N$ respectively.

There are many methods that can be used for nonlinear density equalization, such as point density equalization, stroke crossing number equalization, stroke interval equalization, and overall equalization. Among them, the overall equalization method can most accurately maintain the original shape of calligraphic characters, but this method is very slow. In this paper, the method of stroke crossing number equalization is chosen. This method scans the binarized color matrix of the calligraphic characters in the horizontal and vertical directions, and counts the number of stroke traversals on the scanned lines, which is formally defined as

$$H(i) = \sum_{j=1}^{J} \overline{f(i-1, j)} \cdot f(i, j) + \alpha_H \tag{5}$$

$$V(j) = \sum_{i=1}^{I} \overline{f(i, j-1)} \cdot f(i, j) + \alpha_V \tag{6}$$

The function $f(i, j)$ has value 1 when the point (i, j) is black, and 0 otherwise, with the special $f(i, 0) = f(0, j) = 0$; $\overline{f(i, j)}$ denotes to take the logical non for the binary function $f(i, j)$. The α_H and α_V are two predetermined parameters, both of which are set to 1 here in order to avoid the case where the density is zero.

The nonlinear density function used in this algorithm is global, fast to compute, and little affected by the distribution of strokes in calligraphic characters. Although the nonlinear normalization method based on the number of strokes traversed cannot completely solve the problem of aberration caused by the scaling process, the aberration of one pixel size has a very limited effect on the whole calligraphic character, so the algorithm is very suitable for fast normalization of a large number of calligraphic characters.

2.2 Text structure analysis algorithm

When learning to write Chinese characters, writing rules are very important. The usual writing rules are left before right, up before down, horizontal before vertical, apostrophe before down, inside before outside, center before both sides, door before door, etc. For left and right structures, we usually write all the stroke parts on the left side first, and then write the parts on the right side. For each type of font structure type, we can find the corresponding writing rules. Therefore, when we want to extract the stroke information of the text and use these rules, the prerequisite is to know the structure information of the font first.

2.2.1 Algorithmic constraints

When the skeleton information of the text image is extracted, the pseudo-endpoints and pseudo-clusters must first be removed before the font structure can be analyzed. Here, we use $G = \{g_1, g_2, \ldots, g_n\}$ to define the skeleton graph, and the elements in G are what we call subgraphs, which consist of a set of basic strokes connected to each other by pathways. We analyze the font structure of a text by calculating the relationship between any two subgraphs in G using a positional relation algorithm.

2.2.2 Algorithm implementation

Suppose we want to obtain the positional relationship between the subgraphs g_k and g_l, where g_k is composed of a strokes, which we denote as $\{s_1, s_2, \ldots, s_a\}, g_l$ is composed of b strokes, which we write as $\{s_1, s_2, \ldots, s_b\}$. The positional relationship between two strokes is represented by a dichotomy $R = \{R_h, R_v\}$, where R_h denotes the horizontal positional relationship, and R_v denotes the vertical positional relationship.

Mutual positional relationships can be divided into a total of four categories:
(1) Negative X-axis direction
(2) Positive X-axis direction
(3) Negative Y-axis direction
(4) Positive Y-axis direction

The correspondence between R_h, R_v and the subgraph positional relations is shown in Table 1, which lists all the possible positional relations between g_k and g_l, and the values of R_h, R_v.

Table 1: Correspondence of position relations

	Spatial relationship
R_h =1	g_k is on the left of g_l
R_h =0	g_k is neither on the left side of g_l nor on the right side of g_l
R_h =-1	g_k is on the right of g_l
R_v =1	g_k is above g_l
R_v =0	g_k is neither above g_l nor below g_l
R_v =-1	g_k is below g_l

We compute R_h by the following formula.

$R_h = T(h_l, h_r)$, where $T = \begin{Bmatrix} 1, if\ (h_l > h_r) \\ 0, if\ (h_l = h_r) \\ -1, if\ (h_l < h_r) \end{Bmatrix}$ and h_l denotes the likelihood that g_k is in the g_l negative X-axis direction and h_r denotes the likelihood that g_k is in the g_l positive X-axis direction.

R_v, h_r and h_b are also defined by a similar method water as R_h, h_t and h_r.

In the following we represent h uniformly by h_l, h_r, h_i, and h_b. The h can be computed by the following equation:

$$h = \frac{\sum_{i=1, j=1}^{i=a, j=b} p\Big(f_1(s_i), f_2(s_j)\Big)}{a*b}, s_i \in g_k, s_j \in g_l \tag{7}$$

$$\text{Among them:} \quad p = \begin{cases} 0, if\left(f_1(s_i) \geq f_2(s_j)\right) \\ 1, if\left(f_1(s_i) < f_2(s_j)\right) \end{cases} \tag{8}$$

The functions f_1 and f_2 will have different function definitions depending on the direction, and the definitions of the position functions in the text structure analysis are shown in Table 2.

Table 2: Definition of position function in text structure analysis

Spatial relationship	f_1	f_2
h_l	Max (v_s.x, v_e.x)	Min (v_s'.x, v_e'.x)
h_r	Min (v_s.x, v_e.x)	Max (v_s'.x, v_e'.x)
h_t	Max (v_s.y, v_e.y)	Min (v_s'.y, v_e'.y)
h_b	Min (v_s.y, v_e.y)	Max (v_s'.y, v_e'.y)

Through the above method, we can analyze the font structure information of the text, according to the writing rules, we can know the traversal order of each subgraph, so that the extraction of the stroke order of the text is transformed into the process of extracting the stroke order information for each subgraph.

2.2.3 Algorithm examples

Example 1: Calligraphy character “静(jìng)”.

(1) The first step is to extract the outline of the text image.

(2) Apply the refinement algorithm to the text outline, and peel off the thick lines in the outline layer by layer, and finally get the skeleton information with a width of only one pixel.

(3) According to the skeleton information, the text is composed of 3 subgraphs, the upper left, lower left and right are represented by g_1, g_2, g_3 respectively. After using the font structure analysis algorithm for the 3 subgraphs, the relative positions of the subgraphs are obtained as shown in Table 3.

Table 3: Relative position relationship of subgraphs

Subgraph	R_h	R_v
$g_1 - g_2$	1	0
$g_1 - g_3$	0	1
$g_2 - g_3$	1	0

From the results of the above table, the character is analyzed as a left:right structure, while the upper side is a top-middle-bottom structure.

(4) Combining the writing rules, the stroke order is extracted from the 3 subgraphs according to the smoothness rule in the order of left then right, top then F , i.e. g_1, g_2, g_3.

Example 2: Calligraphy character “清(qīng)”.

(1) The first step is to extract the outline of the text image.

(2) Apply the refinement algorithm to the text outline, and peel off the thick lines in the

outline layer by layer when refining, and finally get the skeleton information whose width is only pixel by pixel.

(3) According to the skeleton information, the text is composed of 4 subgraphs, the top-left j, the middle-left, the bottom-left, and the in-square are represented by g_1, g_2, g_3, g_4, respectively. After using the font structure analysis algorithm for the four subgraphs, the relative positional relationships of the subgraphs are shown in Table 4.

Table 4: Relative position relationship of subgraphs

Subgraph	R_h	R_v
$g_1 - g_2$	0	1
$g_1 - g_3$	1	0
$g_1 - g_4$	1	0
$g_2 - g_3$	0	1
$g_2 - g_4$	0	1
$g_3 - g_4$	0	1

From the results of the above table, the character is analyzed as a left-right structure, while the upper side is a top-middle-bottom structure.

(4) Combine the writing rules, first left and then A_i, first top and then bottom, i.e., the sequential order of g_1, g_2, g_3, g_4 extracts the strokes one by one for the 4 subgraphs according to the smoothness rule.

2.3 Algorithm for Extracting Information of Calligraphy Art

To address the challenges in the extraction of calligraphy art information, this paper proposes the extraction of calligraphy art information based on partition-guided filtering, the algorithm firstly extracts the basic information of the calligraphy characters in the calligraphy sticker image by using the K-nearest neighbor keying algorithm, and then carries out the edge extraction of the calligraphy characters, and then filters the internal region and the edge part of the strokes by using the filtering window of different sizes, and finally obtains the art information extraction results through the pixel level image fusion Finally, the artistic information extraction results are obtained by pixel-level image fusion technology, and the framework process of the method is shown in Fig. 3. The algorithm can accurately extract the characteristics of the ink changes in the stroke area of the calligraphic characters, and it can well maintain the edge details of the calligraphic characters, which greatly improves the accuracy and completeness of the artistic information and promotes the further development of calligraphy digitization.

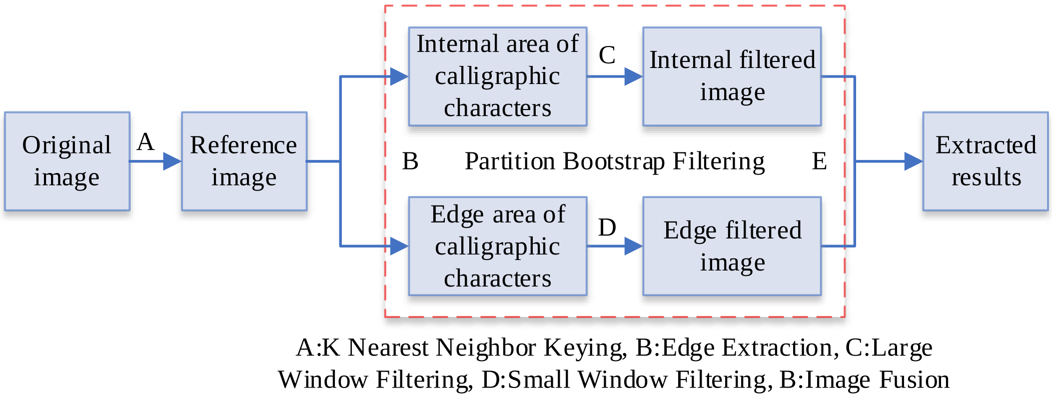


Figure 3: Framework for extracting artistic information

2.3.1 Creating a reference image

For a piece of calligraphy, the complex changes in the ink (e.g., the rapid movement of the dry brush produces the discrete and slight ink) contain a large amount of charm information and are difficult to extract. In order to extract the complete charm information, we use the K-nearest neighbor keying algorithm to extract the basic calligraphic character information in the image, which is used as the reference image for calligraphic character extraction, and lays the foundation for extracting the complex changes of ink strokes in the calligraphic works, and its main process is as follows:

The feature vector is extracted using the color and position information of the image, and the formula is as follows:

$$X(i) = (\cos(h), \sin(h), s, v, x, y)_i \tag{9}$$

where $X(i)$ is the feature vector, h, s, v are the three components of the space of HSV colors, and x, y are the pixel's position coordinates;

Define the kernel function:

$$k(i, j) = 1 - \|X(i) - X(j)\| / C \tag{10}$$

where $k(i, j)$ is the kernel function, $X(i)$ and $X(j)$ are different eigenvectors, and C is the weight adjustment coefficient, which is used to ensure that $k(i, j) \in (0,1)$;

The Laplace matrix is obtained from the kernel function:

$$L = D - A \tag{11}$$

where D is a diagonal matrix and the elements $D_{ii} = \sum_j A_{ij}, A$ on the diagonal of D are similarity matrices;

The closed solution is obtained by adding the user constraint information:

$$\alpha = (L + \lambda M)^{-1}(\lambda V) \tag{12}$$

where M is a diagonal matrix representing the user's labeling of the known pixel points, v is a vector representing the user's labeling of the foreground region, λ is a constraint coefficient, and L is the luminance of the color image in Lab color space;

The reference image is obtained by bringing the value of the closed solution α into the following equation:

$$R = \alpha f + (1-\alpha)b \tag{13}$$

where R is the reference image, f the unknown foreground layer, and b the unknown background layer.

2.3.2 Partitioned bootstrap filtering

The limitation of the bootstrap filtering leads to the inability to get the rich grayscale variations inside the strokes and the accurate and sharp edges of the strokes at the same time. The main reason is that the result of K-nearest neighbor keying is used as the reference image, and the original image of the calligraphy work is the filtering input, and the gray-scale information of the original image can only be restored through the large size of the filtering window, and at the same time, due to the larger window of gradient reduction, it leads to the residue of noise such as the background and the stamp.

We utilize the idea of partitioned statistical modeling to propose the partitioned bootstrap filtering method, the main idea of which is to partition the calligraphy character into two parts, the edge and the interior, which are filtered with different window sizes. Small-size window filtering is applied to the edge to ensure the sharpness and accuracy of the edge; large-size window filtering is applied to the interior to ensure the restoration of rich gray-scale information.

Firstly, this paper utilizes mathematical morphology methods to segment the reference image into two parts: the interior of the stroke and the edge. Corrosion can eliminate the boundary of the object, and a 3×3 matrix is selected to corrode the reference image, so that the edge of the calligraphy character is reduced by one pixel, and then the reference image is used to subtract the corroded reference image, and then the edge of the calligraphy character can be obtained, where:

The corrosion operation is defined as:

$$R \Theta B^S = \left\{Z, B_Z \in R\right\} \tag{14}$$

where R is the reference image, B is a 3×3 structuring element, Z is the transformation distance, B_Z is the result after translating the structuring element by Z units, and B^S is the set of structuring elements symmetric about the origin.

The internal I_{in} of the strokes is calculated as follows:

$$I_{in} = R \odot B = \left\{Z \mid B_z \in R\right\} \tag{15}$$

Then the stroke edge I_e is computed as follows:

$$I_e = R - I_{in} \tag{16}$$

The large size of the filter window leads to noise residues such as background and stamp. Therefore, after separating the edges and the interior of the strokes, the bootstrap filtering process is performed on the edge image with a small window, and the bootstrap filtering process is performed on the interior image of the calligraphic character by choosing the appropriate size of the window to ensure the simultaneous restoration of the rich gray scale variations and the sharp, accurate edges.

A bootstrap filter is a linear transformation of the bootstrap image, i.e:

$$q' = A_k I_g + B_k \tag{17}$$

where q' is the set of corresponding output images and $q' = \{q_{in}, q_e\}, I_g$ is the bootstrap image. A_k and B_k are two sets of linear coefficients, respectively.

To find the optimal linear coefficients, we define the following cost function $E_1(a_{k,1}, b_{k,1})$ in the window φ_k and $E_2(a_{k,2}, b_{k,2})$

$$E_1(a_{k,1}, b_{k,1}) = \sum_{i\in\omega_k}\left(\left(a_{k,1}I_g + b_{k,1} - I_{in}\right)^2 + \varepsilon_1 a_{k,1}^2\right) \tag{18}$$

$$E_2(a_{k,2}, b_{k,2}) = \sum_{i\in\varphi_k}\left(\left(a_{k,2}I_g + b_{k,2} - I_e\right)^2 + \varepsilon_2 a_{k,2}^2\right) \tag{19}$$

where ε_1 and ε_2 are regularization parameters. The optimal solution of the cost function is obtained by linear regression with the following results:

$$\begin{cases} a_{k,1} = \dfrac{\frac{1}{|\omega|}\sum_{i\in\omega_k} I_g I_{in} - \mu_{k,1}\bar{I}_{in}}{\sigma_{k,1}^2 + \varepsilon_1} \\ b_{k,1} = \bar{I}_{in} - a_{k,1}\mu_{k,1} \end{cases} \tag{20}$$

$$\begin{cases} a_{k,2} = \dfrac{\frac{1}{|\varphi|}\sum_{i\in\varphi_k} I_g I_e - \mu_{k,2}\bar{I}_e}{\sigma_{k,2}^2 + \varepsilon_2} \\ b_{k,2} = \bar{I}_e - a_{k,2}\mu_{k,2} \end{cases} \tag{21}$$

Thus, a_k and b_k are of the form:

$$\begin{Bmatrix} A_k \\ B_k \end{Bmatrix} = \begin{Bmatrix} a_{k,1}, a_{k,2} \\ b_{k,1}, b_{k,2} \end{Bmatrix} \tag{22}$$

Then, we calculated the filtered output from the internal regions and edges of the calligraphic characters:

$$\begin{aligned} q_{in} &= \frac{1}{|\omega|}\sum_{k:i\in\omega_k}\left(a_{k,1}I_g + b_{k,1}\right) \\ &= \bar{a}_{i,1}I_{g,i} + \bar{b}_{i,1} \end{aligned} \tag{23}$$

$$\begin{aligned} q_e &= \frac{1}{|\varphi|} \sum_{k:i \in \varphi_k} \left(a_{k,2} I_g + b_{k,2} \right) \\ &= \bar{a}_{i,2} I_{g,i} + \bar{b}_{i,2} \end{aligned} \tag{24}$$

where q_{in} is obtained as the filtering result of the internal region of the calligraphic character, and q_e the filtering result of the stroke edges. In order to obtain the complete information about the artistic information, the image fusion method is defined as:

$$q_{fusion}(x, y) = \min\left(q_{in}(x, y), q_e(x, y)\right) \tag{25}$$

where $\min(\cdot)$ is the operation to obtain the minimum value, and $q_{fusion}(x, y)$ is the final art information extraction result.

3 Application Analysis of Algorithms for Analyzing Calligraphic Art Based on Semiotics

3.1 Calligraphic Character Extraction Process

3.1.1 Width of Calligraphic Strokes at Individual Skeleton Points

Since a stroke is refined into a line with only a single pixel width during the extraction of the calligraphic character skeleton, the stroke width, which expresses the original appearance of the stroke, needs to be extracted. The stroke width is defined as the distance from the skeleton node of the stroke to its corresponding boundary node. The analysis of a skeleton point can know that the boundary point is located in two of the eight directions of the skeleton point. The corresponding directions are divided into four main categories: for horizontal strokes, the boundary points of a stroke are located in different positions in the same column as the skeleton point. For vertical strokes, the boundary points of the strokes are in different positions in the same row as the skeleton point. For the withdrawing and pressing strokes, the boundary points of the strokes are in the direction of the two diagonal lines at right angles to the skeleton point. According to the above analysis, the width of the stroke where a skeleton point is located is related to the type of the stroke it is located in, and the method of selecting the width of the stroke corresponds to the strokes of different stretching directions is also different. However, the width of a stroke should correspond to a specific stroke trend, and among the four stroke widths calculated at the same skeleton point, only the one that corresponds to the stroke trend is the most suitable for the stroke, and it is also the shortest stroke width.

To obtain the width of a stroke at a certain skeleton point, start from the upper left neighborhood of the skeleton point and traverse the eight neighborhoods of the skeleton point in a clockwise direction to the boundary nodes respectively. Record the number of nodes traversed in each traversal, which are denoted as $n_1, n_2 \ldots\ldots n_8$. Divide these 8 values into four groups: $g_l, g_2, \ldots\ldots, g_4$, where $g_i = n_i + n_{i+4}$. Take half of the minimum value in g_i as the width value of the calligraphy character at this point. Take the Chinese character "口(kǒu)" as an example. The stroke widths of each point in its skeleton are shown in Figure 4. The stroke width of the "口(kǒu)" character is mainly concentrated in the range of 5 to 10mm, and a few discrete points reflect the turning or endpoint characteristics of the strokes.

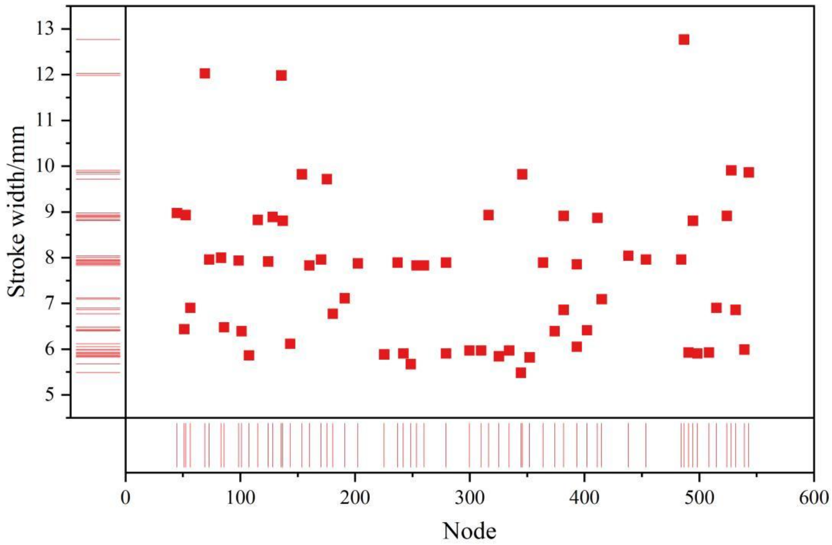


Figure 4: Width of strokes at each point of the framework

3.1.2 Stroke Extraction

Any non-terminal node in the skeleton of a stroke divides the stroke into two ordered parts, i.e. the node is the tail node of one stroke segment and the start node of the other. According to the writing habit of calligraphy characters, the beginning node of a stroke is completed before the end node. In general, the logical position of the first stroke point in the matrix of calligraphic characters is smaller than that of the second stroke point. Therefore, if the stroke segments divided by a certain point all start or end at that point (the logical position of the point is the smallest or the largest), then this node connects two different strokes, so you need to remove the set of strokes in this case again, and in this case, you only need to decompose the strokes on both sides of the point. However, because calligraphers always have their own style in the creative process, like to have twisted strokes, resulting in a direct result of the completion of the stroke points after the logical distance is not necessarily greater than that of the first completion of the stroke points, the logical position of the points on the skeleton of the word "口(kǒu)" and the vertical and horizontal coordinates of the relationship shown in Figure 5. The logical position increases slowly with increasing nodes, reflecting the continuity of the calligraphic order of strokes.

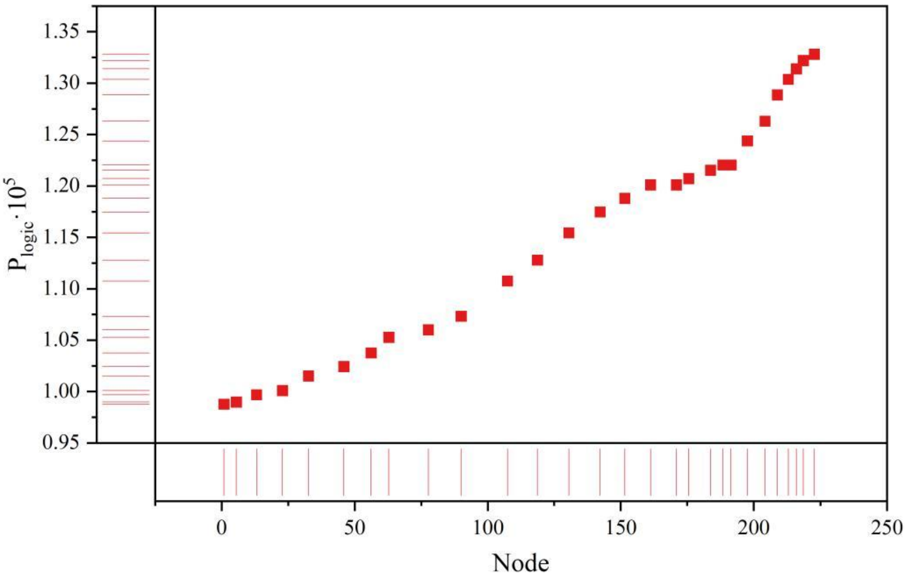


Figure 5: The logical positions of each point on the framework

3.1.3 Classification of stroke segments

Further, using wavelet transform, the vertical projection map was smoothed to establish the segmentation point. The results of vertical projection and wavelet transform fitting of the character "口(kǒu)" are shown in Fig. 6, where the horizontal coordinates indicate the pixel positions of the same horizontal coordinates in the vertical direction, and the vertical coordinates indicate the statistical values of the number of the same horizontal coordinates. It can be clearly seen that the very small value point at the wave valley roughly cuts out the segmentation position of the calligraphy character, and the subsequent paper is categorized according to the location of the very small value of the wave valley.

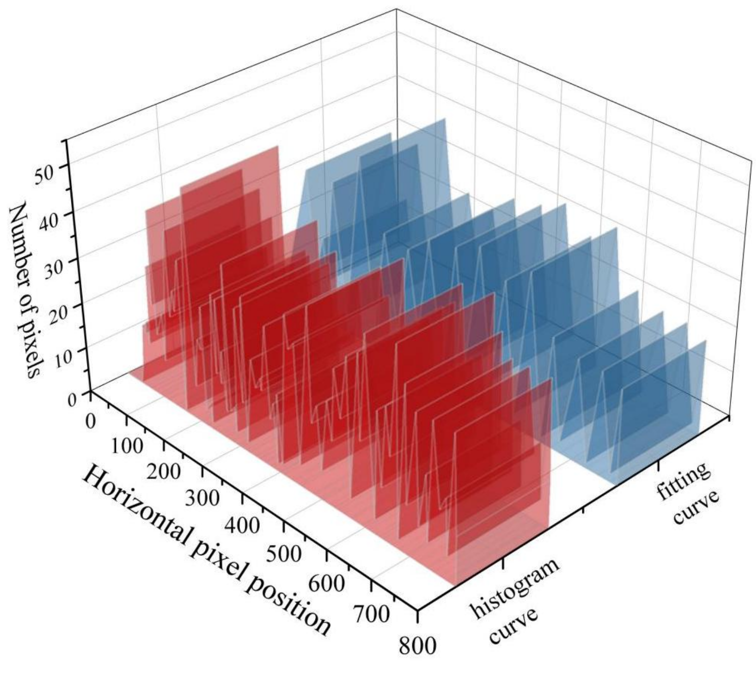


Figure 6: Vertical projection and wavelet transform fitting results

3.1.4 Extraction of results

For the analysis of the dark low contrast region, the results of the comparison between the brightness high contrast region's and the dark low contrast local region are shown in Fig. 7. The results show that the difference between the grayscale values of the front and back view of the dark low-contrast region is very small, so the method of this paper can be used to further extract the information of the stroke segment of the calligraphic character, and transform the single-pixel binarization problem into a clustered pixel classification problem, which finally realizes the extraction of the calligraphic character "口(kǒu)".

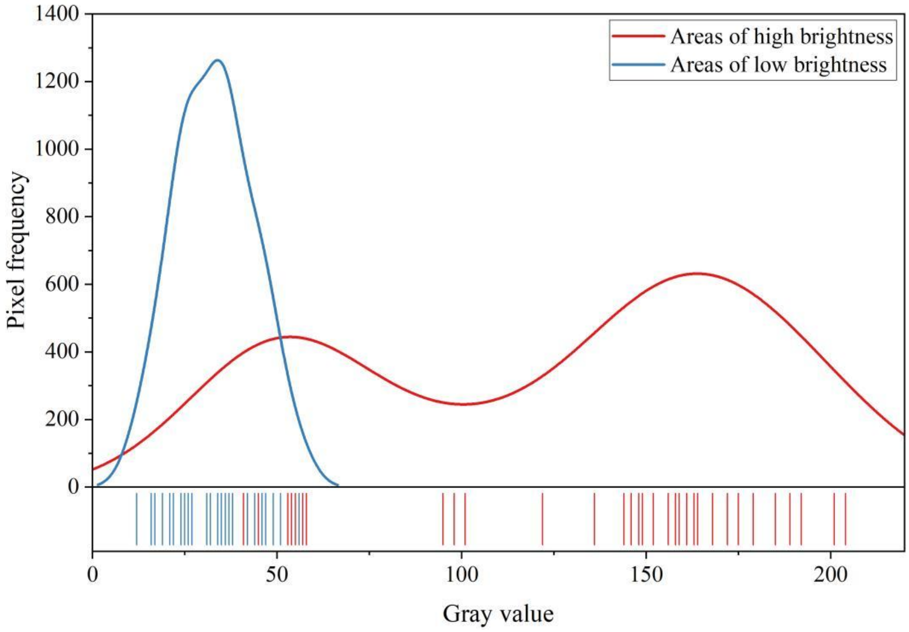


Figure 7: Comparison results of local areas with different contrast levels

3.2 Performance testing

In this paper, we randomly select 2500 Chinese characters from 5863 italic characters written by calligraphers, and then randomly select 2500 Chinese characters from 165,785,562 italic copy characters written by students, and self-constructed calligraphy dataset for experiments.

3.2.1 Burr detection performance

The operations of preprocessing and skeleton extraction of the calligraphic characters in the dataset result in 5000 Chinese character skeletons, but not every skeleton contains burrs. After screening, 1235 Chinese character skeletons containing burrs are obtained. After counting, these 1235 skeletons contain 2534 burrs. The sample set of the experiments in this section is 1235 Chinese character skeletons and 2534 burrs.

The algorithm of this paper is compared experimentally with the threshold method, the significance-ordered pruning method and the automatic pruning method, and the results of the burr detection performance comparison are shown in Table 5. The algorithm in this paper has the best overall performance in the burr detection task, with an accuracy of 99.27%, which is significantly higher than that of the threshold method (97.32%), the significance-ordered pruning method (80.13%) and the automatic pruning method (94.92%). The accuracy of Chinese character processing is 98.42%, and the processing speed reaches 20.11 characters/second, which ensures high accuracy and real-time performance at the same time.

Table 5: Comparison results of edge detection performance

	Accuracy rate of burr detection (%)	Blunt edge defect detection rate (%)	Accuracy rate of Chinese character processing (%)	Error rate in handling Chinese characters (%)	Processing speed (characters per second)
Threshold method	97.32	2.68	70.27	29.73	41.23
Significant sorting pruning method	80.13	19.87	68.94	31.06	16.44
Automatic pruning method	94.92	5.08	91.05	8.95	29.38
The proposed	99.27	0.73	98.42	1.58	20.11

3.2.2 Skeleton extraction performance

Algorithms A and B are mainstream advanced skeleton extraction algorithms. Algorithm A uses Kmeans++ clustering algorithm for intersection clustering and reconnecting strokes and PBOD algorithm for fuzzy region detection. Algorithm B performs stroke matching by judging the slope relationship between stroke segments when reconstructing strokes, and detects fuzzy regions using the maximum circle. In addition, this paper also introduces two traditional skeleton extraction algorithms, respectively SSGAN and its variant algorithm CSEGAN and this paper's algorithm for comparison test, five different algorithms of the skeleton extraction performance comparison results shown in Table 6. This paper's algorithm stroke skeleton accuracy rate of 99.04%, the Chinese character skeleton error rate of only 4.22%, processing speed of 8.93 characters / second, in the balance between accuracy and efficiency, confirming the algorithm's ability to effectively deal with complex stroke connections and fuzzy regions.

Table 6: Comparison results of skeleton extraction performance

	Accuracy rate of stroke framework (%)	Stroke skeleton error rate (%)	Accuracy rate of Chinese character skeleton structure (%)	Error rate of Chinese character skeleton structure (%)	Processing speed (characters per second)
Algorithm A	92.75	7.25	86.47	13.53	11.38
Algorithm B	95.91	4.09	92.15	7.85	14.65
SSGAN	93.27	6.73	87.38	12.62	10.93
CSEGAN	95.88	4.12	92.71	7.29	15.38
The proposed	99.04	0.96	95.78	4.22	8.93

3.2.3 Quantitative comparison results

In the generator's loss function, the L1 loss is used to generate the low-frequency part of the image, and the hyperparameter λ is used to balance the Gan loss and the L1 loss. To verify the reasonableness of setting the value of λ to 20 in the objective function, the comparison results of the changes in the L1 loss function with different values of λ are shown in Fig. 8. Training in the case of $\lambda = 10$, the loss fluctuation is more drastic and the position is high in the late stage. Whereas, there is almost no significant difference between the cases of λ at 20, 30, 40 as well as 50, and the final L1 loss values are all around 0.03. Therefore, it is considered that in the task of this paper, λ takes an insensitive value and the default value of 20 is used.

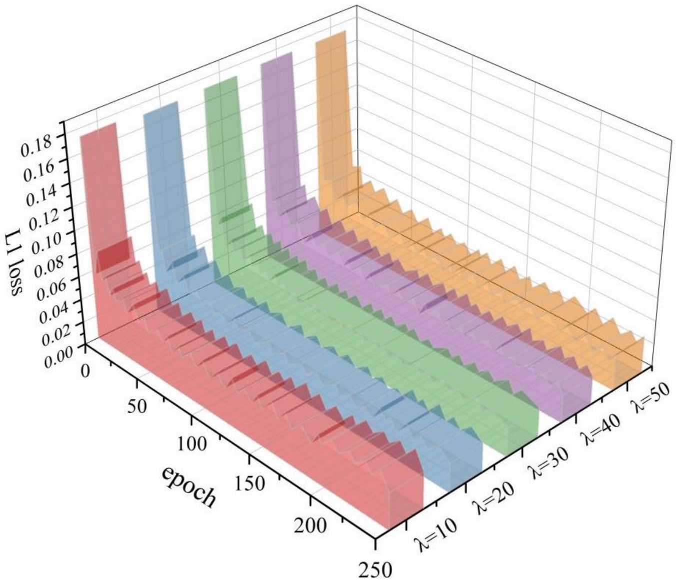


Figure 8: Comparative results of the L1 loss function under different λ values

Further comparison experiments are conducted with other existing skeleton extraction methods, and the quantitative comparison results of five different algorithms on the self-constructed dataset are shown in Table 7. Compared with other algorithms, this paper's algorithm has obvious improvement in the indexes, with F1 and IoU of 0.7018 and 0.5264, respectively, which shows that the overall structure of the skeleton image generated by the network is better, and the accuracy of skeleton localization is higher.

Table 7: Quantitative comparison results

	ACC	Recall	Precision	F1	IoU	OAMD
Algorithm A	0.9538	0.6836	0.6364	0.3486	0.1976	0.5937
Algorithm B	0.9736	0.7722	0.7542	0.6617	0.4786	0.2183
SSGAN	0.9422	0.6735	0.6611	0.3035	0.1835	0.6176
CSEGAN	0.9687	0.7634	0.7456	0.6534	0.4622	0.2264
The proposed	0.9891	0.8162	0.8118	0.7018	0.5264	0.1386

4 Conclusion

In this paper, we have successfully constructed a digitization method system for calligraphic art covering preprocessing, structural analysis and artistic information extraction, and proved the effectiveness of the proposed method through experiments.

In the burr detection task, the algorithm in this paper has the best overall performance, with an accuracy of 99.27%, which is significantly higher than that of the threshold method (97.32%), the significance-ordered pruning method (80.13%) and the automatic pruning method (94.92%). The accuracy of Chinese character processing is 98.42%, and the processing speed reaches 20.11 characters/second. In the skeleton extraction task, this paper's algorithm has a stroke skeleton accuracy rate of 99.04%, a Chinese character skeleton error rate of only 4.22%, and a processing speed of 8.93 characters/second, which strikes a balance between accuracy and efficiency, and confirms the algorithm's ability to effectively deal with complex stroke connections and fuzzy regions. Compared with other algorithms, this paper's algorithm has a significant improvement in the indexes in the quantitative comparison experiments, with F1 and IoU of 0.7018 and 0.5264, respectively, which shows that the overall structure of the skeleton image generated by the network is better, and the accuracy of skeleton localization is higher.

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