Writing process restoration of Chinese calligraphy images based on skeleton extraction

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Abstract. In this paper, a writing process restoration method for static Chinese calligraphy works is proposed. Through this method, the initial skeleton of the Chinese character calligraphy image is extracted first. Then, the distortion elimination and sorting processes are performed for the initial skeleton, and the accurate skeleton of the Chinese character image is obtained. Finally, the appropriate ink dots are selected to move and render along the skeleton, thus obtaining the dynamic writing effects. Regarding the aspect of skeleton distortion elimination, the initial skeletons are first classified into three different types; then, the processing algorithms are designed respectively according to their morphological features, thus realizing highly efficient recognition and elimination for the skeleton distortion. This method can realize rapid dynamic restoration for calligraphy fonts, such as regular script.

1. Introduction

Chinese character calligraphy art is an important part of traditional Chinese culture. However, both calligraphy masters’ works at all different ages and the calligraphy copybooks in the market are static. They cannot satisfy the demands of people for the appreciation, teaching, and learning of calligraphy. Therefore, many studies have been carried out to achieve the dynamic restoration of Chinese character calligraphy images.

For example, Zhuang et al.\textsuperscript{[1]} segmented the strokes of Chinese character images, and then sorted the segmented strokes according to cognitive knowledge for generating the writing effects. Zhang et al.\textsuperscript{[2]} focused on the stroke shape and writing effects in the restoration process. These methods had deficiencies when it comes to accuracy and efficiency. Therefore, we propose the idea of writing process restoration based on Chinese character skeleton extraction. The main steps in the process consist of the extraction of the Chinese character skeleton, the elimination of skeleton distortion, and the reconstruction of the writing order.

Regarding the extraction of the Chinese character skeleton, many methods have been proposed. For example, the Periphery Outline Method \textsuperscript{[3]}, the Segmentation Method \textsuperscript{[4][5]}, the Region Decomposition Method \textsuperscript{[6]}, the Fuzzy Area Detection Method \textsuperscript{[7]}, and the Neural Network Method \textsuperscript{[8]}. Among these methods, most of them were proposed for the recognition of printed Chinese characters, and they could not be applied to the written calligraphy of Chinese characters.

Existing studies regarding the aspect of distortion elimination of the Chinese character skeleton are rare. For instance, Xun et al.\textsuperscript{[9]} adopted a knowledge engineering method to establish an independent distortion elimination rule for each Chinese character, but this method had low efficiency. Zhao et al.\textsuperscript{[10]} recognized the distortion of Chinese character skeleton according to the estimated handwriting stroke width, but the processing effect of this method was limited and it could not solve all distortion
problems.

Regarding the reconstruction of the writing order, Li et al. [11] proposed a reconstruction method of handwriting the number stroke order, but this method can only be applied to character sets with low complexity, such as numbers. In addition, Belongie et al. [12] proposed a shape matching algorithm based on the context of the shape and the key points of the image, and then reconstructed the order of the Chinese character strokes.

In view of the key problems stated above, a new solution is presented in this paper. First, the initial Chinese character skeleton is obtained by basic methods, such as thinning algorithms. Then, the initial skeletons are classified into three types: rough stroke, long stroke, and inside short stroke segments. Next, the distortion elimination algorithms are designed according to the morphological features for the three kinds of skeletons, respectively, and thus the recognition and elimination of distortion is realized automatically and with high efficiency. Finally, the appropriate ink dots are used to move along and fill the sorted Chinese character skeleton. Thus, the animated display of the writing process can be realized. The advantage of this method is that it can automatically recognize and remove the distortion in the Chinese character skeleton, and restore the writing process with high efficiency.

2. Extraction of the initial skeleton
For the static nature of calligraphy characters, the purpose of this step is to obtain the initial Chinese character shape skeleton. The following operations are included in this step: preprocessing, thinning, and the extraction of skeleton segments.

2.1 Pre-processing
Firstly, the original calligraphy copybooks are scanned to obtain digital images. Then, the operations of graying, binarization, and smoothing are performed on the images. Common methods of the binarization process include two categories: the overall threshold method (e.g., the OTSU algorithm [13]) and the local threshold method (e.g., the region growing method [14]). In this paper, according to the overall light and shade effects, a calligraphy work image is segmented by regions; then the OTSU algorithm is used to process each region, respectively; and finally, the processing results of each region are merged and the binarization result is achieved.

2.2 Thinning Algorithm
The common thinning algorithms include the Sherman thinning algorithm [15], the rapid and parallel thinning algorithm by Zhang [16], and the OPTA algorithm [17]. However, these methods are not sufficient. For example, the algorithm by Zhang cannot guarantee the thinning results as single pixel path, and the OPTA algorithm can easily generate many useless branches. To ensure that the Chinese character skeleton fits the writing center line as much as possible, and to avoid the breakage of strokes, the Rosenfeld thinning algorithm [18] is selected. Figure 1 shows the processing results of a regular script Chinese character “Song”, in which (a) is the binarization result and (b) is the thinning result.

2.3 Extraction of the skeleton segments
First, the skeletons after thinning algorithms are expressed as a pixel sequence \{p_1, p_2, \ldots, p_n\}, and then this sequence is segmented into a series of stroke segments. The detailed operations consist of the three steps described below.

(1) Traversing all the pixels in the skeleton. For any skeleton pixel \(p\), it is marked as below.

In its eight connected regions, if the number of other skeleton pixels is two, then \(p\) is marked as an internal point; otherwise, \(p\) is marked as an endpoint. For example, Figure 2 amplifies the four local regions of a skeleton image. In regions A and B, the black pixels represent internal points, and the slash shaded points represent endpoints.
(2) According to the mark results, the skeleton stroke segments set \( S = \{ s_1, s_2, \ldots, s_n \} \) is obtained, in which \( s_i = \{ u, w_1, w_2, \ldots, w_j, \ldots, v \} \). Here, \( u \) and \( v \) come from the endpoint set, and \( w_j \) are between \( u \) and \( v \) and are the internal points successively adjacent to each other.

(3) For each skeleton stroke segment obtained in the previous step, the dynamic ray algorithm\(^{[19]}\) is used to calculate its inflection points set \( T = \{ t_1, t_2, \ldots \} \). The skeleton stroke segment is further divided based on these inflection points. For example, in region C of Figure 2, the slash shaded pixel is an inflection point that divides the original skeleton stroke segment into two parts. While there is no inflection point in region D of Figure 2.

After the processing steps described above, the initial skeleton stroke segments set is obtained. For example, Figure 3 is the extraction result of the skeleton stroke segments of the Chinese character “Song” in Figure 1(b). Among them, the dot represents the vertex, and the white line between the two adjacent vertexes represents a stroke segment.

![Figure 1](image1.png)  ![Figure 2](image2.png)  ![Figure 3](image3.png)

Figure 1. The processing results of the calligraphy Chinese character “song”.
Figure 2. Pixel classification of the skeleton.
Figure 3. The extraction results of skeleton stroke segments of “song”.

3. Distortion elimination and sorting of initial skeletons
As shown in Figure 3, the initial skeleton has distortion at the stroke intersection, the turn, and in other places. Therefore, it cannot be directly applied to the restoration of the writing process. In this section, the distortion recognition and elimination are performed, and then the final skeletons are sorted.

3.1 Classification of the initial skeleton stroke segments
The following Definitions are presented first in this section.

- The length of certain skeleton stroke segment \( s \) is marked as \( l_s \), which represents the number of pixels in the stroke segment \( s \).
- The handwriting width of the skeleton stroke segment \( s \) is marked as \( w_s \), which represents the handwriting width of the center point of this stroke segment. The calculation method is given below: At the center of \( s \) in the binary image, the two boundary points of this stroke are found along the normal direction of \( s \); and the distance between the two points is the handwriting width of \( s \).
- The average handwriting width of the whole Chinese character is marked as \( W_c \) which represents the average value of the handwriting width of the longest \( m \) stroke segments of the whole character. Here, \( m \) is an empirical value.
- The adjacent attribute of the skeleton stroke segment \( s \) is marked as \( (a_s, b_s) \), which means the beginning point of \( s \) is adjacent to \( a_s \) other stroke segments, and the endpoint is adjacent to \( b_s \) other stroke segments.

In this section, the initial skeleton stroke segment sets are classified into rough stroke segments, inside short stroke segments, and long stroke segments based on the definitions above. As shown in Figure 4, for a specific stroke segment \( s \): 1) If its adjacent attribute is \( (0, 2) \) or \( (2, 0) \), then the relation among its length, width, and the threshold is further estimated; and if it satisfies the estimation conditions, then it is marked as a rough stroke segment type; otherwise, it is marked as a long stroke segment type. 2) If its adjacent attribute is \( (2, 2) \), then the relation among its length, width, and the threshold is also estimated, and whether it satisfies the triangle principle is estimated at the same time. If it satisfies the estimation conditions, then it is marked as an inside short stroke segment type; otherwise, it is marked as a long stroke segment type. 3) If its adjacent relation is other conditions,
then it is directly marked as a long stroke segment type. The thresholds \( \alpha, \beta, \) and \( \gamma \) in the figure are obtained based on sample training.

![Figure 4. The classification process of skeleton stroke segments.](image)

It should be noted that the “triangle principle estimation” in Figure 4 is proposed in this paper according to the morphological features of Chinese character strokes. The specific operations for the stroke segment \( s \) are given below:

1. Starting from an endpoint \( P \) of \( s \), a depth-first traverse is performed for the adjacent skeleton stroke segments, and the points set of all the points that have the path distance \( l \) with Point \( P \), marked as \( E^P = \{E_i^P\} \), \( i=1,2,\ldots \).

2. Starting from another endpoint \( Q \) of \( s \), a depth-first traverse is performed for the adjacent skeleton stroke segments, and the points set of all the points that have the path distance \( l \) with Point \( Q \), marked as \( E^Q = \{E_j^Q\} \), \( j=1,2,\ldots \).

3. Traversing the following triangles: \( \Delta P Q E^P_1, \Delta P Q E^P_2, \ldots, \Delta Q P E^Q_1, \Delta Q P E^Q_2, \ldots \). For the binary image of the calligraphy, if the pixels in the all triangle regions above are all the stroke color, then it indicates that the stroke segment \( s \) satisfies the triangle principle; otherwise, the stroke segment \( s \) does not satisfy it.

Consider the following example as shown in Figure 5(a). The endpoints of \( s \), which is the stroke segment to be handled, are \( P \) and \( Q \). The set of the points that have path distance \( l \) with \( P \) is \( \{E_1, E_2\} \), and the one with \( Q \) is \( \{E_3, E_4, E_5\} \). Therefore, the triangles to be traversed are \( \Delta P Q E_1, \Delta P Q E_2, \Delta P Q E_3, \Delta P Q E_4 \) and \( \Delta P Q E_5 \) (as shown in Figure 10(b-f)).

![Figure 5. A diagram of triangle principle.](image)

3.2 Processing of the inside short stroke segment

The inside short stroke segments are the distortion led by the stroke intersection. Therefore, the processing purpose is as follows: delete the inside short stroke segments; smoothly connect the other long stroke segments adjacent to them; and make the result consistent with the center line of the original stroke.
First, grouping is performed based on the following rules: For the inside short stroke segment $s_i$, we traverse other inside stroke segments adjacent with it, and if the inside stroke segment $s_j$ can be accessed after a series of traverses, then $s_i$ and $s_j$ are in the same group. For example, one inside short stroke segment marked by the dotted line circle in Figure 6(a) forms a group and three inside short stroke segments marked by the dotted line circle in Figure 6(c) form a group.

For some Group $G$, the set of all other segments adjacent to it is $S_G = \{S_{iG}\}, i=1,2..., N$, and then the processing method for Group $G$ is given below:

1) Calculate Group $G$’s bounding box’s center point coordinates ($x=m$, $y=n$), and delete the $G$ in the initial skeleton stroke segment $S$.

2) For each stroke segment $S_{iG}$ of $S_G$, delete its part skeleton pixels which have the length of $W \times \beta_G$ ($\beta_G$ is some zoom factor) at its end adjacent to $G$.

3) Traverse the arbitrary two-stroke segments $S_{iG}$ and $S_{jG}$ in $S_G$, and if they can fit as a smooth segment without turning points, then Hermit Curve\[^{[20]}\] is used to connect them together and merge them as one stroke segment.

4) For the remaining stroke segments that cannot merge in $S_G$, they are lengthened until they intersect with the straight line $x=n$ or $y=m$.

By using the Hermit Curve, we can guarantee the processed results are consistency with the center lines of the original strokes. Figure 6 presents two cases in which (a) and (c) are original skeleton stroke segments, and (b) and (d) are the processed results.

3.3 Processing of the rough stroke segments
Rough stroke segments have two types: One is led by the stroke turn, as shown in Figure 7(a); and the other is formed by stroke adhesion, as shown in Figure 7(b). The processing methods for the two kinds of rough stroke segments are different. Therefore, the types of the rough stroke segments should be recognized. In this paper, it is recognized by the Chinese character handwriting habits and the geometrical parameters (e.g., the angle and direction) between the rough stroke segments and the adjacent segments.

3.3.1 Processing of the rough stroke segments led by stroke turn. For the rough stroke segment $s$ led by stroke turn, its endpoints are marked as $M$ and $N$, and its adjacent two segments are marked as $S_{1MN}$ and $S_{2MN}$, as shown in Figure 8(a). We need delete $s$, and adjust $S_{1MN}$ and $S_{2MN}$ to make them consistent with the center line of the original stroke. The specific operations are given below:
(1) For stroke segments \( S_1^{MN} \) and \( S_2^{MN} \), delete their part skeleton pixels which have the length of \( l \times \alpha_s \) (\( \alpha_s \) is the zoom factor) at the end adjacent to \( s \). Two new stroke segments, \( S_A^{MN} \) and \( S_B^{MN} \), with endpoints \( A \) and \( B \) are obtained, as shown in Figure 8(b).

(2) An appropriate point \( C \) in the extending line of \( s \) is selected.

(3) Hermit Curve is used to connect \( AC \), and merge \( AC \) and \( S_A^{MN} \) into one stroke segment. Likewise, Hermit Curve is used to connect \( BC \), and merge \( BC \) and \( S_B^{MN} \) into one stroke segment. At the same time, rough stroke segment \( s \) is deleted, as shown in Figures 8(c) and 8(d).

Figure 9(a) shows the result of processing the rough stroke segments in Figure 7(a) using the method above.

3.3.2 Processing of the rough stroke segments formed by stroke adhesion. For the rough stroke segments formed by stroke adhesion, they need to be merged with some adjacent stroke segments. The necessary smooth adjustments should also be carried out at the same time. The adjustment method here is like the one in the last section, that is, the distortion part in the stroke segment is first deleted and then Hermit Curve is used to make a smooth connection. Figure 9(b) presents the results of processing Figure 7(b).

3.4 Processing of the long stroke segments

The phenomenon of three long stroke segments gathering in the same point may exist in the set of the skeleton stroke segments. This is caused by over-segmentation of the stroke segments, which does not conform to real writing habits. In view of this condition, the two-stroke segments with over-segmentation need to be merged, and smooth operations for the adjacent stroke segments need to be performed. Figure 10 presents an effects comparison of the long stroke segments before and after processing.

![Figure 9](image1.png)

(a) Figure 9. An example of the result of processing the rough stroke segments.

![Figure 10](image2.png)

(b) Figure 10. An example of the processing of long stroke segments.

Here, all the adjustment operations have been accomplished. At this point, the set of skeleton stroke segments are formed according to the stroke starting point, the end point, and the turning point during the writing process of Chinese characters. Therefore, they conform to the dynamic restoration demands of static Chinese calligraphy, and there is no over-segmentation or insufficient segmentation. In addition, their paths can fit the original writing tracks well.

3.5 Sorting of the skeleton stroke segments

After distortion elimination, the skeleton stroke segments are arranged in a disorderly manner. Here, the Relaxation Matching Algorithm\(^{[21]}\) is adopted to realize the order of skeleton stroke segments.

First, a standard character library is established. The character library stores the standard stroke path and writing order of each Chinese character. It should be noted that this information is irrelevant to the specific writing style. Afterward, the previous skeleton stroke segments are matched with the Chinese characters in the standard character library. Then, the correct ordering of the skeleton stroke segments can be realized.

4. Writing process restoration

We need select an appropriate ink dot, and then move and fill it along the correctly-ordered skeleton stroke segments. Thus, the dynamic restoration of Chinese character calligraphy can be realized. As an
example, a round stroke shape can be considered, with the detailed steps provided below.

(1) Based on the ordered skeleton stroke segments, each pixel in the skeleton stroke segment is traversed.

(2) For some skeleton pixel \( A \), its stroke radius \( w_A \) is calculated according to the binary image.

(3) Taking \( A \) as the center of circle and \( w_A \) as radius, a roundness is generated in a blank image; then, the pixel values within this round area in the original calligraphy image are copied to the blank image.

Figure 11 presents the dynamic writing process of Chinese character “Song”.

Figure 11. Writing process restoration of Chinese character “Song”.

5. Experimental analysis

Regular script, which is characterized by its upright and foursquare style, is the commonly-used method of handwriting upright letters in modern society. Therefore, we chose two styles of regular script, and selected 101 samples for each style respectively. These samples were scanned to be images, and then they were used to verify our method. Part of the samples of these two styles are shown in Figure 12, in which the structure of sample A is wide and flat, and includes more pausing strokes and back strokes while the structure of sample B is thin and long, with smooth strokes.

Based on our method, 148 samples could obtain the correct skeletons, and satisfactory writing restoration was achieved. The specific data is shown in the second column of Table 1. Figure 13 presents more writing restoration results achieved by our method.

Figure 12. Calligraphy samples with two styles.

Figure 13. Examples of writing restoration.

| Number of correct samples | Number of correct samples after adding interactions |
|---------------------------|---------------------------------------------------|
| Sample A 70/101 (69.3%)   | 84/101 (83.2%)                                    |
| Sample B 78/101 (77.2%)   | 92/101 (91.1%)                                    |

Some of the failed samples were caused by stroke adhesion. As shown in Figure 14(a), the two
parts marked by circles were adhered together during the writing process. This resulted in the skeleton results displayed in Figure 14(b), which do not conform to the correct handwriting tracks. For this reason, an interaction tool was added for the program in which users can adopt a manual method to cut off a stroke. The processed correct results are shown in Figure 14(c). The experimental data after adding the interaction tool is shown in the third column of Table 1.

It is known from the third column of Table 1 that some samples still could not correctly realize writing restoration. After analysis, it was found that the reasons for failure include three aspects:

Firstly, the classification of the initial skeletons had errors. In the 202 experimental samples, there were 318 short stroke segments, 193 rough stroke segments, and 387 triple points of long stroke segments were recognized in total. Among them, the recognition of rough stroke segments and long stroke segments were all correct while the ones of inside short segments had eight groups of errors, referring to six Chinese characters. This kind of classification error generally occurred in the Chinese characters that had relatively intense strokes and complicated intersection relations.

Secondly, the morphological features of some stroke combinations were not obvious during the distortion elimination process. As shown in Figure 15, (a) is the original skeleton, (b) is the skeleton after distortion elimination, and (c) is correct handwriting skeleton. From the perspective of static images, there is no obvious morphological difference between (b) and (c); therefore, it may perform wrong smooth connections for the two irrelevant segments under this condition.

Lastly, there were pausing strokes and back strokes in the calligraphy characters. These phenomena make the Chinese character strokes generate unnecessary segments at the endpoint or result in overlapping at the turning point. Both can lead to errors in skeleton extraction. As shown in Figure 16, (a) is the original skeleton, (b) is the skeleton after distortion elimination, and (c) is the correct handwriting skeleton. This leads to bad experimental data for Sample A as shown in Table 1.

In the future, the writing rules of Chinese characters are expected to be analyzed to solve the above-stated problems.

![Figure 15. A stroke combination without obvious morphological features.](image1.png)

![Figure 16. Cases of pausing strokes and back strokes.](image2.png)

6. Conclusion
The main contribution of this paper is presenting an effective extraction algorithm for calligraphy character skeleton segments. In view of various distortions after thinning, the proposed method classifies the initial skeletons into three types. Then, it uses Hermit Curve to perform smooth processing for the distortion. It realizes the writing process restoration of calligraphy characters based on the skeleton segments after distortion elimination, and it has a rather high correctness of restoration. Future work includes sample training according to the writing habits of Chinese characters to efficiently process the calligraphy characters with phenomena such as back strokes or joined strokes.

Acknowledgements
This research project is supported by Wu Tong Innovation Platform of Beijing Language and Culture University (supported by “the Fundamental Research Funds for the Central Universities”) (16PT04) and the Research Funds of Beijing Language and Culture University (supported by “the Fundamental Research Funds for the Central Universities”) (18YCX015).

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