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A Method of Calligraphy Style Transfer

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Abstract

This paper proposes a method of calligraphy style transfer which can generate the specified style. Firstly, the calligraphy characters input by users are retrieved from the calligraphy database, the feature extraction of layouts, characters and strokes for calligraphy style measurement, and the similarity between the calligraphy character style and the user specified style is calculated; secondly, when the character needed by the user can not be retrieved in the calligraphy database, the radicals or strokes of the calligraphy characters are decomposed, and the radicals and strokes similar to the target style are retrieved from the calligraphy library for synthesis; finally, all the calligraphy characters with the target style are arranged on the page to generate a complete work. Experiments are carried out with 1389 single character images in CADAL calligraphy database. The results show that the method can generate high-quality calligraphy characters of specified style with correct structures.

Keywords

Style transfer; Style similarity; Calligraphy character synthesis.

1. Introduction

Nowadays, people are keen to pursue individualization. Whether in dress or behavior, everyone seeks their own unique style. Similarly, on computers and mobile phones, many people use individual themes to show their uniqueness. Personalized themes on mobile or computers include personalized fonts. Although these fonts different from standard fonts, users have limited choices. In many cases, users are not satisfied with the existing fonts but cannot create their own favorite fonts. If a font style transfer system can be used to generate any designated style font, so that everyone can have a personalized font.

The key of calligraphy style transfer is the style representation and style transfer. style representation can be divided in Chinese characters and non-Chinese characters. In the field of Chinese characters, Yu [1] expressed the calligraphy character style from three aspects: the layouts, strokes, structure and radicals, but in this research, it is assumed that calligraphy style of all works is the same, so it may loss features such as stroke shape; Wang [2] in the study of calligraphy style recognition divided the calligraphy style features into word-level features and stroke-level features, but the stroke-level features only included vertical strokes and horizontal strokes, the other strokes may also affect the result. In the field of non-Chinese characters, Azmi [3] proposed the use of unequal triangles to extract features in the Arabic calligraphy classification task, but the structure of Arabic calligraphy and Chinese calligraphy is quite different, and this method is not suitable for feature extraction of Chinese calligraphy; Bar-Yosef [4] carried out feature extraction of ancient Hebrew calligraphy characters to identify the address, date and author in works of different handwriting styles. This method can be used for Chinese character strokes, but not for more complex strokes; Senobari [5] used wavelet transform and sobel-robert operator to extract the features of Persian fonts to realize the recognition of Persian. The features extracted by this method are not suitable for the style transfer of calligraphy characters.

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In terms of style transfer, with the development of neural network, new ideas and methods have been brought to the task of image style transfer. Gatys [6] first proposed use Gram matrix to quantify the image style, and used the image iterative synthesis method based on the VGG[7] to complete the image style transfer; Dumoulin[8] found that by changing γ and β parameters of IN (Instance Normalization) layer , the network can be used to train and learn different styles of pictures; Zhu [9] proposed a new Generative Adversarial Networks (GAN)---CycleGAN, which does not need to quantify the style, the image style can be transferred. Many scholars were inspired by image style transfer and used neural networks in the task of font style transfer. Tian [10] uses Convolutional Neural Networks (CNN) to build a Chinese character style transfer model. Due to the different data distributions of different style features, the same CNN cannot fit well on differently distributed data. Therefore, the model can only transfer one style; Zi2zi [11] adds category embedding and multi-class category loss to the traditional GAN so that the model can learn multiple font styles; SCFont [12] divides the font style transfer into two part: using CNN for font handwriting transfer and GAN for style rendering, this method reduces the structural dislocation of the generated font; AGIS-Net [13] uses two parallel encoder-decoder branches to complete the structure and texture transfer of art fonts at the same time in a single stage; Li [14] introduced the CGAN to the Mongolian character style transfer task for the first time, and realized the automatic transfer of Mongolian character style; MC-GAN [15] proposed a leave-one-out training method to automatically generate a large number of letters with the same style from a small number of English letters. The above methods have migrated the styles of handwriting, artistic characters, and different languages, but more or less there are problems such as low quality of the generated image, and the sticking or disconnection of the strokes of the generated characters, or even the confusion.

In order to obtain clear and distinctly generated calligraphy characters, this paper proposes a style transfer system for calligraphy characters, which extracts features from the three levels of calligraphy works: layout, characters, and strokes. After character retrieval, radical retrieval and synthesis, stroke retrieval and synthesis, the page layout of all characters is carried out to complete the transfer from font style to page layout style.

2. System Architecture

The architecture of the calligraphy style migration system is shown in Figure 1. First, build a calligraphy style database to provide a data basis for style transfer. Extract the page features of the calligraphy works, then segment the pages of the work to obtain each calligraphy character, and extract the style features of the calligraphy characters; then segment the calligraphy characters to obtain radicals and extract the radical features; finally segment the radicals to obtain strokes and extract stroke features. User enters a calligraphy work, selects the target style, the system performs page analysis on the input work, extracts the calligraphy characters, and searches calligraphy characters from calligraphy style database according to the target style. If the retrieval is successful, select the calligraphy character closest to the target style and search for the next character. Otherwise, perform radical decomposition search; if all the radicals that make up the character can be retrieved successfully, the appropriate radicals will be combined and measure the similarity of the target style. If similar, search for the next character. Otherwise, decompose the radicals into strokes and search. At the same time, obtain the radical and stroke composition of the corresponding reference character; the strokes of the target style are scaled according to the size of the reference strokes, and the radicals are formed according to the position of the reference strokes in the radicals, and then the radicals are used for font synthesis. After the style transfer of all the characters from input work is completed, the page layout is performed and generate a work with the target style layout.

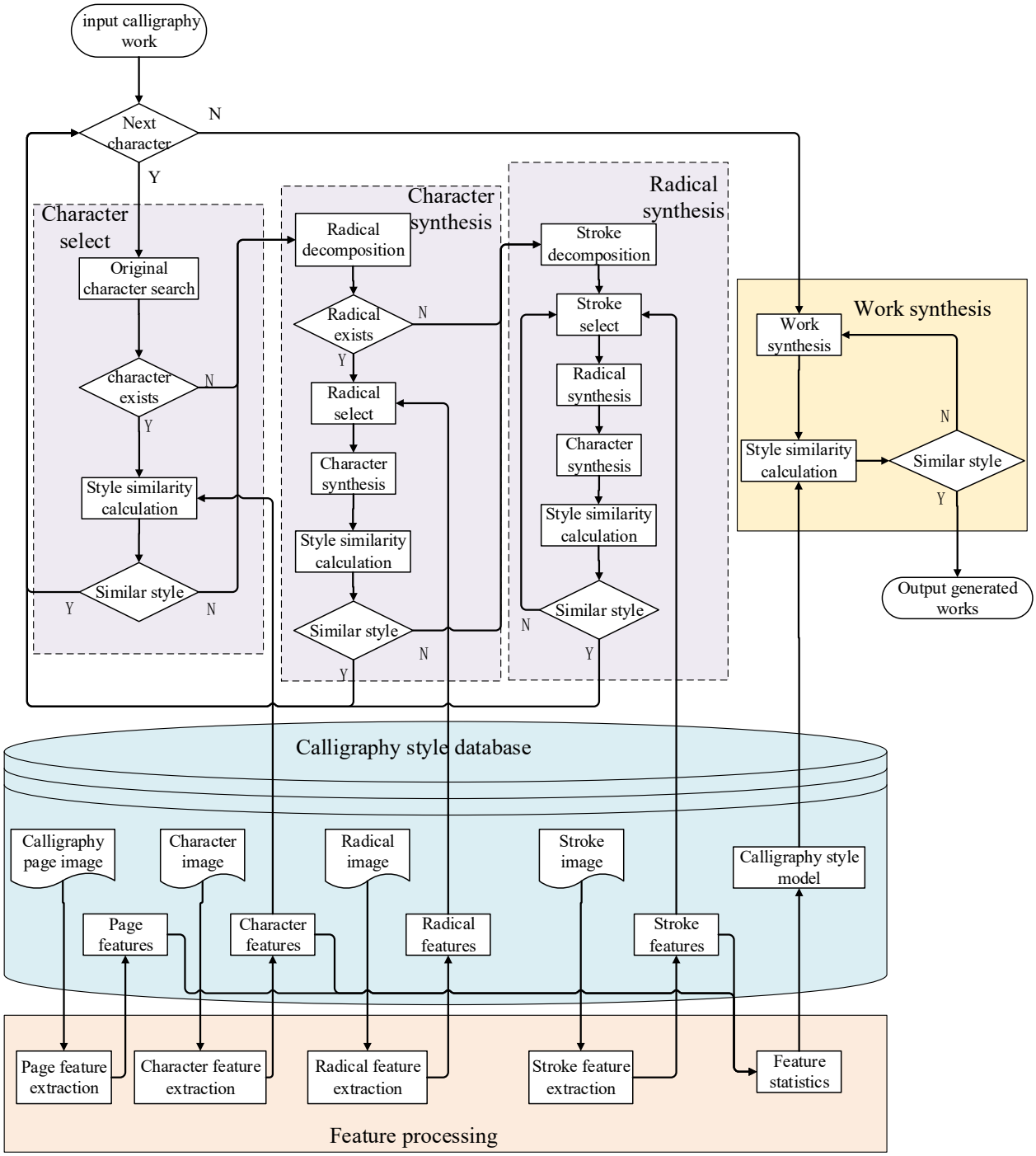

Figure 1. System Architecture

3. Style Representation

3.1. Layout Features

Character distance. The distance between the minimum bounding box of characters and the minimum bounding box of its top, bottom, left, and right adjacent characters. To avoid repetition, the distance between the right and bottom adjacent characters is taken as the character distance. dx is right distance, dy is bottom distance, so character distance is $D_c = (dx, dy)$.

Row-column distance. Row distance and column distance in calligraphy works. In different calligraphy works, the page layout is different, and the row-column distance is the most

intuitive feature. Suppose that there are n rows and m columns on a page, $dx_{i,j}$ is the right character distance of i-th row and j-th column in the calligraphy work, $dy_{i,j}$ is the bottom character distance of i-th row and j-th column in the calligraphy work, $1 \le i \le n$, $1 \le j \le m$. The row distance D_{row} and column distance D_{col} are:

$$\begin{cases} D_{row} = \dfrac{1}{mn}\sum_{i=1}^{n}\sum_{j=1}^{m} dy_{i,j} \\ D_{col} = \dfrac{1}{mn}\sum_{i=1}^{n}\sum_{j=1}^{m} dx_{i,j} \end{cases}.$$

The row-column distance is $D_w = \left(D_{row},\ D_{col}\right)$.

Deviation degree of the center. When writing calligraphy, the centers of a row of characters is basically on the same line, as shown in Figure 2. Taking the average center of a row of characters as the baseline X, the deviation degree of the center of each character in the line is $H = G_x - X$.

Figure 2. Deviation degree of the center. The dashed line is the baseline and the triangle is the center

3.2. Character Features

Aspect ratio. The aspect ratio of calligraphy characters, $V = h / w$, where h is the height of the calligraphy characters and w is the width of the calligraphy characters.

Area ratio. The proportion of calligraphy character pixels in its binary image, $S = N / N_s$ where N is the number of character pixels, and N_s is the number of all pixels in the binary image.

Center of character. Suppose $f\left(x, y\right)$ is the image function, the center of image is:

$$\begin{cases} G_x = M_{10} / M_{00} \\ G_y = M_{01} / M_{00} \end{cases}$$

We can use the following equation to calculate M:

$$M_{p,q} = \sum_{x=0}^{w-1}\sum_{y=0}^{h-1} x^p y^q f\left(x, y\right)$$

And the center is $G = \left(G_x / w, G_y / h\right)$.

Average stroke width. The average of the width of all strokes in a calligraphy character. Suppose the area of all strokes of a calligraphy character is S_{area}, replaced by the total number of stroke

pixels, S_{length} is the number of outline pixels of the calligraphy character, and the average stroke width can be expressed by the formula [1] $W = \frac{S_{area}}{S_{length}} \times 2 + 1$.

Radical position. When the same radical is in different positions, its size and shape may change, $p = (RG, (topX, topY))$,where RG is the center of radical and $(\text{top}X, topY)$ is the coordinates of the upper left corner of the minimum bounding box of the radical.

3.3. Stroke Features

Width of ends of the stroke. The width is expressed by the distance from the point on the skeleton of the stroke to the outline of the stroke. Take the point on the skeleton that is the average stroke width from the two ends as the center of the circle. The initial radius is $r = 0.5$, the radius is increased according to the ratio of the number of scenic spots in the circle and the total number of pixels in the circle. When the ratio is less than the threshold 0.95, the radius stops increasing,, and the width of the beginning and end of the stroke is expressed as $b = (r_{smax}, r_{emax})$, where r_{smax} is the width of the beginning of the stroke, and r_{emax} is the width of the end of the stroke.

Thickness of strokes. Use the distance from the point on the stroke skeleton to the stroke outline to indicate the thickness of the stroke. Suppose there are a total of n points for the stroke skeleton, then:

$$\begin{cases} Z_\mu = \frac{1}{n}\sum_{i=1}^{1} r_i \\ Z_\sigma = \frac{1}{n}\sum_{i=1}^{1} (r_i - Z_\mu)^2 \end{cases}.$$

Where Z_μ represents the mean of the distance from the skeleton point of the stroke to the outline, and Z_σ represents the variance of the distance from the skeleton point of the stroke to the outline.

Stroke deviation. The degree to which a stroke deviates from a straight line, it can be expressed by equation $q = l_s / l$, Where l_s is the number of pixels of the stroke skeleton, and l is the length of the connecting segment between the two ends of the stroke skeleton.

Stroke aspect ratio. Like aspect ratio of calligraphy characters, $sv = sw / sh$, where sh is the height of the stroke and sw is the width of the stroke.

Stroke position. The position of strokes in calligraphy characters, $sp = (topSX, topSY)$, $(\text{top}SX, topSY)$ is the coordinates of the upper left corner of the minimum bounding box of the stroke.

4. Style Transfer

According to the target style specified, the calligraphy work input by the user is converted into a calligraphy work with the target style. The whole conversion process is divided into four main steps: character selection, new style calligraphy character synthesis, new style calligraphy character radical synthesis and layout style transfer.

4.1. Character Selection

We use the style features of Chapter 3 to measure feature similarity, include layout features $z=(D_c,H)$,character features $t=(V,S,G,W,p)$, stroke features $s=(Z_\sigma,b,q,sv,sp)$. Since the styles of different works of the same author may be different, whether the retrieved characters and the converted characters are from the same work will also be a feature. The target style is the reference object. The average value and standard deviation of the feature components of all target styles are calculated, and the average value is used as the reference feature, so the target style vector is:

$$F_{ref}=\left(\overline{D_c},\overline{H},\overline{V},\overline{S},\overline{G},\overline{W},\overline{p},\overline{Z_\sigma},\overline{b},\overline{q},\overline{sv},\overline{sp}\right)$$

Suppose f is a feature component of calligraphy characters, f_{ref} is the feature component corresponding to F_{ref}, its standard deviation is sd_{ref}, and the normalization formula is $f'=\frac{f-f_{ref}}{sd_{ref}}$. The style feature is normalized to $z'=(D_c',H')$, $t'=(V',S',G',W',p')$, $s'=(Z_\sigma',b',q',sv',sp')$. The work to which the character belongs is another feature, so the style feature vector of the calligraphy character can be expressed as $C=(z',t',s',w)$, where w is the work that the character belongs to. Suppose C_i, C_j are the feature vectors of two different calligraphy characters, $C_i=(z_i',t_i',s_i',w_i)$, $C_j=(z_j',t_j',s_j',w_j)$, and the style similarity between them is calculated by the following formula:

$$SIM_C=a_1Z\left(z_i',z_j'\right)+a_2T\left(t_i',t_j'\right)+a_3S\left(s_i',s_j'\right)+a_4G\left(w_i,w_j\right)$$

Where $\alpha_1+\alpha_2+\alpha_3+\alpha_4=1$; $Z\left(z_i',z_j'\right)$, $T\left(t_i',t_j'\right)$, $S\left(s_i',s_j'\right)$ are the feature similarity of layout, character and stroke between two different calligraphy characters, they can be measured by Euclidean distance:

$$\begin{cases} Z\left(z_i',z_j'\right)=\sqrt{\left(z_i'-z_j'\right)\left(z_i'-z_j'\right)^T}, \\ T\left(t_i',t_j'\right)=\sqrt{\left(t_i'-t_j'\right)\left(t_i'-t_j'\right)^T}, \\ S\left(s_i',s_j'\right)=\sqrt{\left(s_i'-s_j'\right)\left(s_i'-s_j'\right)^T}. \end{cases}$$

$G\left(w_i,w_j\right)$ indicates whether two characters belong to the same work:

$$G\left(w_i,w_j\right)=\begin{cases} 0, w_i=w_j \\ 1, else \end{cases}$$

The more similar the styles of the two characters, the smaller the value of SIM_C.

4.2. New Style Calligraphy Character Synthesis

Some calligraphy characters cannot be found in the calligraphy database for their corresponding styles. these calligraphy characters are decomposed into radicals, and the appropriate corresponding radicals are selected from the database, and then the calligraphy characters are synthesized according to the features such as the position of the radical. In order to ensure that the character features are the same as the overall style features, the position and size need to be adjusted.

Radical selection. When the radical is selected, the similarity calculation will be performed from the five features of the radical, include radical stroke complexity c, radical position p, radical

stroke width rw, radical aspect ratio v, and the work to which the radical belongs. The radical stroke complexity is the ratio of the number of strokes to the number of strokes of a character. Suppose the original radical feature vector is $R=(c,p,v)$, the target radical feature vector is $R_t=(c_t,p_t,rw_t,v_t,w_t)$, the matching degree calculation formula is:

$$M_R=\lambda_1 RC(c_t,c)+\lambda_2 RP(p_t,p)+\lambda_3 RW(rw_t,W_f)+\lambda_4 RV(v_t,v)+\lambda_5 RG(w_t,w_f)$$

Where $\lambda_1+\lambda_2+\lambda_3+\lambda_4+\lambda_5=1$, W_f is the average stroke width of the target style reference character, w_f is the work that target style reference character belongs to. The functions in the formula are defined:

$$\begin{cases} RC(c_t,c)=|c_t-c|, \\ RP(p_t,p)=\sqrt{(p_t-p)(p_t-p)^T}, \\ RW(rw_t,W_f)=|rw_t-W_f|, \\ RV(v_t,v)=|v_t-v|, \\ RG(w_i,w_j)=\begin{cases} 0, w_t=W_f \\ 1, else \end{cases}. \end{cases}$$

Where $RC(c_t,c)$ is whether the stroke complexity of the original radical and the target radical are the same, $RP(p_t,p)$ is whether the original radical and target radical are in the same position, $RW(rw_t,W_f)$ is whether the stroke width of the target radical is the same as the stroke width of the target style reference character, $RV(v_t,v)$ is whether the size of the original radical and the target radical are the same, $RG(w_t,w_f)$ is whether the target radical and reference character are from the same work.

a b c

Figure 3. Radical position adjustment and optimization

Character synthesis. After the corresponding radicals are obtained, they are synthesized according to the position of the original radicals in the calligraphy characters. Since the size of the target radicals is inconsistent with the size of the original radicals, the radicals may overlap during the synthesis process (Figure 3a). Therefore, in the synthesis process, the initial distance dr between the radicals needs to be increased (Figure 3b). Although the radical adhesion is avoided by increasing the initial distance, the difference between the style of the whole character and the target style will increase, and the position of the radical needs to be further

adjusted (Figure 3c). Suppose the initial center of the radical is $\left(G_{s.x}, G_{s.y}\right)$, the center after adjusting the position of the radical is $\left(G_{s.x}^{'}, G_{s.y}^{'}\right)$, after adjusting the position of the radicals, the center of the synthesized calligraphy characters is $\left(G_{x}^{'}, G_{y}^{'}\right)$, the average center of all calligraphy characters in the work where the target style reference character in is $\left(\overline{G_{f.x}}, \overline{G_{f.y}}\right)$, and standard deviation of the center is $\left(\sigma_{f.x}, \sigma_{f.y}\right)$,. The position adjustment formula is:

$$\left|G_{x}^{'} - \overline{G_{f.x}}\right| \le \delta_{x}, \quad 0 \le \delta_{x} \le \sigma_{f.x}$$

$$\left|G_{y}^{'} - \overline{G_{f.y}}\right| \le \delta_{y}, \quad 0 \le \delta_{y} \le \sigma_{f.y}$$

$$\left|G_{s.x}^{'} - G_{s.x}\right| \le a_{1}$$

$$\left|G_{s.y}^{'} - G_{s.y}\right| \le a_{2}$$

Where a_1, a_2 is constants. Take the radical with the smallest coordinate value of the upper left vertex of the smallest bounding box among all radicals as the reference radical, and adjust the position of other radicals. The first inequality and the second inequality are used to check whether the center of the character after adjustment is close to the average center of the target style character. If the position of the center is not within the acceptable range, continue to adjust. The horizontal and vertical coordinate adjustment step is 1 pixel, until the center falls within the acceptable range. The third inequality and the fourth inequality ensure that the relative position of each radical in the character cannot be excessively shifted during the adjustment process.

4.3. New Style Calligraphy Character Radical Synthesis

When there are no radicals that make up calligraphy characters in the radical database, the radicals are decomposed into strokes. This part is divided into two steps: select the appropriate strokes from the stroke database, and compose the corresponding radicals.

Stroke selection. In the selection of strokes, in addition to the width of the ends of the stroke b, the degree of twisting of the stroke q, the aspect ratio of the stroke sv, and the position of the stroke sp, the width of the stroke sp will also be taken into account as an important feature. Suppose the original stroke feature vector is $S = \left(b, q, sv, sp\right)$, the target stroke feature vector is $S^{'} = \left(b^{'}, q^{'}, sv^{'}, sp^{'}, sw\right)$, the average stroke width of the work where the target style reference character in is $\overline{W_f}$, and the measurement formula is:

$$M_{s} = \omega_{1} B\left(b, b^{'}\right) + \omega_{2} Q\left(q, q^{'}\right) + \omega_{3} SV\left(sv, sv^{'}\right) + \omega_{4} SP\left(sp, sp^{'}\right) + \omega_{5} SW\left(sw, \overline{W_f}\right)$$

Where $\omega_1 + \omega_2 + \omega_3 + \omega_4 + \omega_5 = 1$, the functions in the formula are defined:

$$\begin{cases} B\left(b, b^{'}\right) = \left|b - b^{'}\right|, \\ Q\left(q, q^{'}\right) = \left|q - q^{'}\right|, \\ SV\left(sv, sv^{'}\right) = \left|sv - sv^{'}\right|, \\ SP\left(sp, sp^{'}\right) = \sqrt{\left(sp_{x} - sp_{x}^{'}\right)^{2} + \left(sp_{y} - sp_{y}^{'}\right)^{2}}, \\ SW\left(sw, \overline{W_f}\right) = \left|sw - \overline{W_f}\right|. \end{cases}$$

Radical synthesis. Strokes synthesis radicals need to know the position and size of the strokes in the radicals. Although the original radicals contain this information, the radicals synthesized with this information will obviously have the features of the original radicals, so the original radicals cannot be used as a reference. Our method uses standard font that style similar to the target style as a reference to synthesize radicals. Taking the generation of the radical "gua" of character "gu" as an example (Figure 4), first obtain the character "gu" from the standard font file, and then obtain the position of the radical "gua" in the standard character, which is represented by the smallest bounding box of the strokes. The strokes retrieved from the database are scaled to the corresponding standard stroke size, and then these strokes are synthesized according to their positions in the standard radical to obtain a complete target radical. After that, the synthesized radicals are synthesized into complete calligraphy characters according to the radical synthesis method.

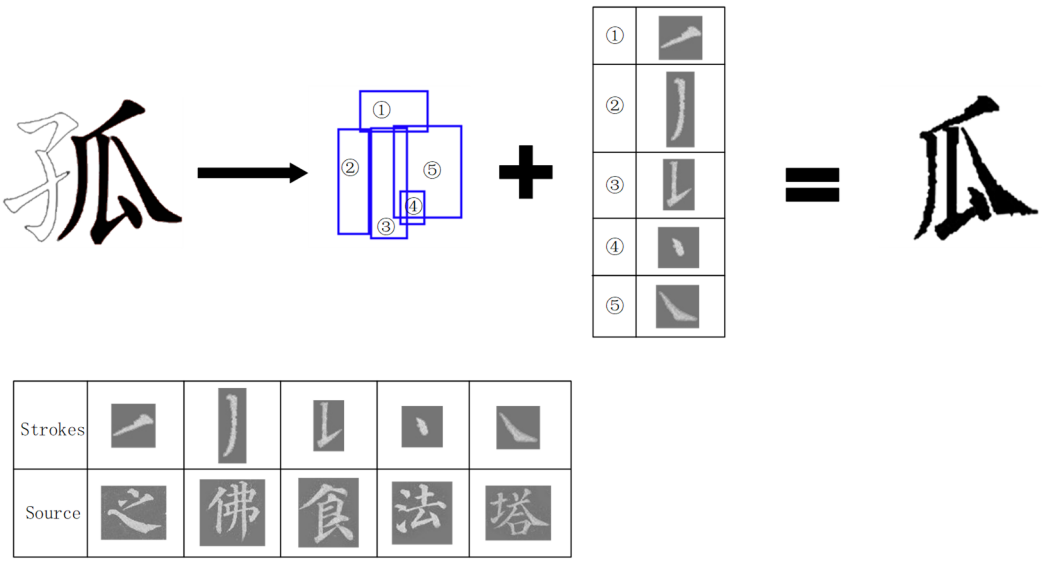

Figure 4. Progress of radical synthesis

4.4. Layout Style Transfer

The layout style of calligraphy works will be affected by factors such as page size and written content, but in the same work, the layout style tends to be the same. The layout style is mainly reflected in row-column distance and whether the center of a column of characters on a straight line. Suppose the abscissa H_{ref} of the center of the first character in each line of the generated work be the baseline, the adjusted abscissa of the center of the remaining characters is G_{nx}, the adjusted row and column distance is $\left(D'_{nrow}, D'_{ncol}\right)$, the row and column of the target style is $\left(D'_{row}, D'_{col}\right)$, the following formula should be satisfied after each adjustment:

$$\left|G_{nx} - H_{ref}\right| \le \varepsilon$$

$$\left|D'_{nrow} - D'_{row}\right| \le \sigma_r$$

$$\left|D'_{ncol} - D'_{col}\right| \le \sigma_c$$

Where ε is constant, σ_r and σ_c are the standard deviations of the row-column distance of the target style respectively. In fact, the center of the characters in each line does not need to be on a straight line, it can deviate slightly (the first inequality). The row and column distance of the generated works should be similar to the target style (the second and third inequality).

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5. Experiment and Results

The target style of this calligraphy style transfer experiment is the calligraphy style of Yan Zhenqing (a famous calligrapher in ancient China). Use the work of Ou yangxun as input for style transfer experiments. The output of the system is the synthesized work after the transfer is completed. As is shown in Figure 5, the left is the input calligraphy work, the middle is the synthesized calligraphy work, and the right is the target style calligraphy work.

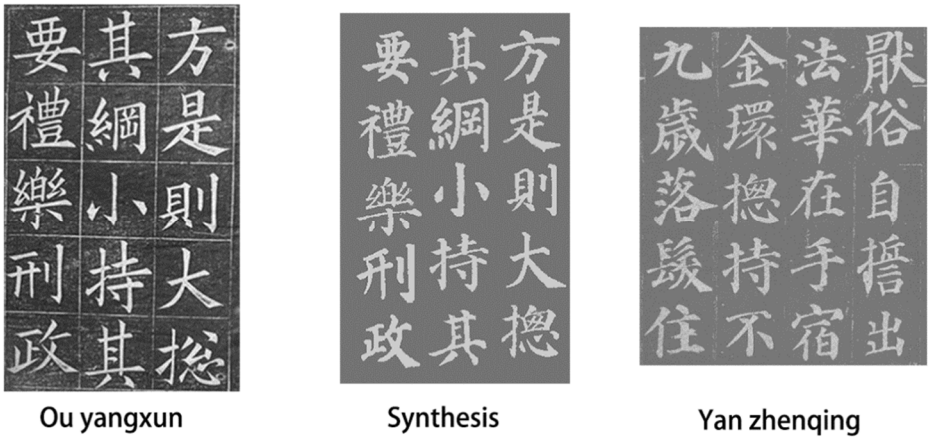

Figure 5. Synthesis result

6. Conclusion

This paper proposes a complete system of calligraphy style transfer. By extracting the style features of calligraphy layout, character and stroke, the style of one calligraphy character is transferred to another, and the calligraphy works with the target style are generated. Experiments show that our method is reasonable and effective.

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