World Scientific Research Journal Volume 7 Issue 5, 2021
ISSN: 2472-3703 DOI: 10.6911/WSRJ.202105_7(5).0048

# Hierarchical-based Calligraphy Style Transfer

Jianyong Cao[1, a]

[1]School of Information Engineering, Shanghai Maritime University, 201306, Shanghai, China

[a]jy.cao.wcm@outlook.com

## Abstract

**This paper proposes a calligraphy style transfer method based on hierarchical structure which can generate the specified style. Firstly, extract the style features from the three levels of calligraphy's layout, characters and strokes, and build a calligraphy style database. Then, the calligraphy characters input by users are retrieved from the calligraphy database. If the character needed by the user can not be retrieved in the calligraphy database, 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 show that the method is effective and efficient for calligraphy characters and works synthesis.**

## Keywords

**Style transfer; Style similarity; Calligraphy character synthesis.**

## 1. INTRODUCTION

The fonts on computers and mobile phones are limited. If users want a personalized font that they like, they have almost no way to get it. If a font style transfer system can be used to generate any designated style font, so that everyone can have a personalized font.

The researches on the transfer of calligraphy style started very early. Wong [1] proposed a three-dimensional calligraphy brush model in 2000, which uses a cone shape as the brush model; Based on [1], Xu [2] decomposed the brush tip into several brush clusters, reduce the computational complexity. Wu [3] proposed a web application for the reproduction of three-dimensional calligraphy writing using the width of the strokes of calligraphy characters and the order of calligraphy writing. Methods in [1, 2, 3] can well restore the original style of calligraphers, but can only generate existing calligraphy characters, and cannot generate new calligraphy characters. Yu [4] proposed a 3-level hierarchical calligraphy character model, the synthesis result is measured by the style evaluation model. Zhang [5] proposed a font outline generation method based on Chinese calligraphy historical documents. Velek [6] proposed a method of online generation of Chinese characters. According to the handwriting input by the user, different types of Chinese character pictures were generated through constant line model, proportional model and calligraphy model. Shi [7] proposed a calligraphy character generation method that combines the contour features of calligraphy characters and the contour features of computer fonts. [4, 5, 6, 7] although can generate new calligraphy characters, it is necessary to accurately extract the style features of calligraphy characters. Tian [8] 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 [9] adds category embedding and multi-class category loss to the traditional GAN so that the model can learn multiple font styles; SCFont [10] divides the font style transfer into two part: using CNN for font handwriting transfer and GAN for style rendering, this method reduces the structural

ISSN: 2472-3703 DOI: 10.6911/WSRJ.202105_7(5).0048

dislocation of the generated font; AGIS-Net [11] 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 [12] 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 [13] 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 methods use neural network [8, 9, 10, 11, 12, 13] can carry out rapid style migration, but it needs a lot of high-quality original data to accurately extract style features. Due to the long history of ancient calligraphy, the integrity and clarity of calligraphy characters are poor, and the number of reserved calligraphy characters is not enough.

This paper proposes a style transfer system for calligraphy characters, which extracts features from the three levels of calligraphy works: layout, character, and stroke. 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 character style to page layout style.

## 2. SYSTEM ARCHITECTURE

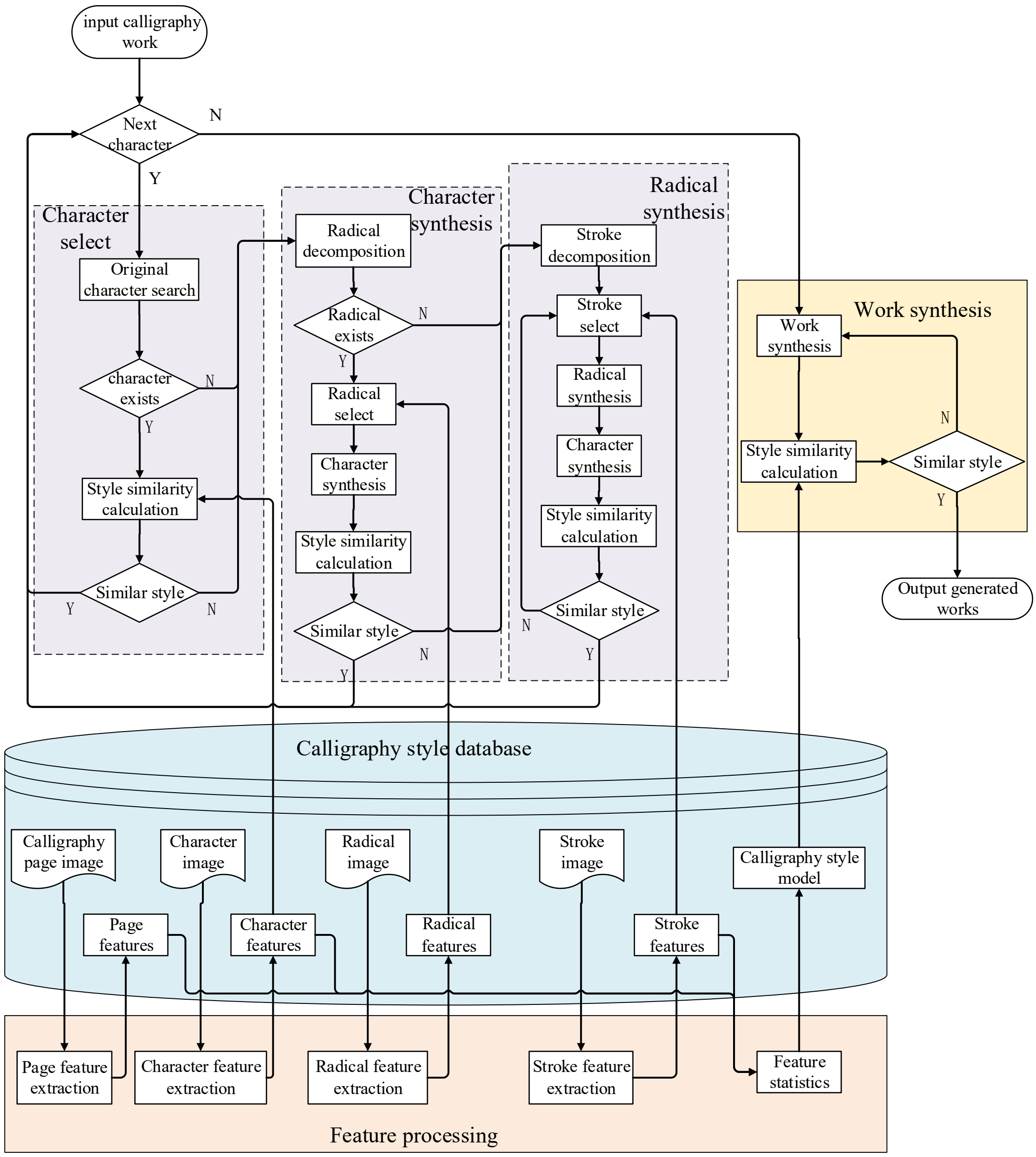


**Figure 1.** System Architecture

ISSN: 2472-3703 DOI: 10.6911/WSRJ.202105_7(5).0048

The architecture of the calligraphy style transfer system is shown in Figure 1. First, build a calligraphy style database to provide a data basis for style transfer. Extract the page features, character features, radical features and stroke features of calligraphy works, calligraphy characters, radicals and strokes, respectively. User enters a calligraphy work, selects the target style, the system performs page analysis on the input work, extracts the calligraphy characters. In character selection part, retrieve suitable character from calligraphy style database according to the target style. In character synthesis part, decompose the radicals of calligraphy characters that are not in the database, then radicals used to synthesis calligraphy character. In radical synthesis part, decompose the strokes of radicals that are not in the database. The strokes of the target style are scaled according to the size of the reference strokes, and the radicals are generated according to the position of the reference strokes in the radicals. Then the radicals are used for font synthesis. In work synthesis part, all characters used to generate a work with the target style layout.

# 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:

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

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

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

ISSN: 2472-3703 DOI: 10.6911/WSRJ.202105_7(5).0048

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

## 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.

Centroid of character. Suppose $f(x, y)$ is the image function, the centroid of image is:

$$\begin{cases} G_x = M_{10} / M_{00} \\ G_y = M_{01} / M_{00} \end{cases} \tag{2}$$

We can use the following equation to calculate $M$ :

$$M_{p,q} = \sum_{x=0}^{w-1} \sum_{y=0}^{h-1} x^p y^q f(x, y) \tag{3}$$

And the centroid is $G = (G_x / w, G_y / h)$.

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 centroid of radical and $(\mathrm{top}X, topY)$ 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 centroid 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:

ISSN: 2472-3703 DOI: 10.6911/WSRJ.202105_7(5).0048

$$\begin{cases} Z_{\mu} = \frac{1}{n}\sum_{i=1}^{1} r_i \\ Z_{\sigma} = \frac{1}{n}\sum_{i=1}^{1}\left(r_i - Z_{\mu}\right)^2 \end{cases}. \tag{4}$$

Where $Z_{\mu}$ represents the mean of the distance from the skeleton point of the stroke to the outline, and $Z_{\sigma}$ 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, $sp = (topSX, topSY)$, $(\text{topS}X, topSY)$ 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

ISSN: 2472-3703 DOI: 10.6911/WSRJ.202105_7(5).0048

calligraphy characters, $C_i = \left(z_i^{'}, t_i^{'}, s_i^{'}, w_i\right)$, $C_j = \left(z_j^{'}, t_j^{'}, s_j^{'}, w_j\right)$, and the style similarity between them is calculated by the following formula:

$$SIM_C = a_1 Z\left(z_i^{'}, z_j^{'}\right) + a_2 T\left(t_i^{'}, t_j^{'}\right) + a_3 S\left(s_i^{'}, s_j^{'}\right) + a_4 G\left(w_i, w_j\right) \tag{5}$$

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:

$$\begin{cases} Z\left(z_i^{'}, z_j^{'}\right) = \sqrt{\left(z_i^{'} - z_j^{'}\right)\left(z_i^{'} - z_j^{'}\right)^T}, \\ T\left(t_i^{'}, t_j^{'}\right) = \sqrt{\left(t_i^{'} - t_j^{'}\right)\left(t_i^{'} - t_j^{'}\right)^T}, \\ S\left(s_i^{'}, s_j^{'}\right) = \sqrt{\left(s_i^{'} - s_j^{'}\right)\left(s_i^{'} - s_j^{'}\right)^T}. \end{cases} \tag{6}$$

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

$$G\left(w_i, w_j\right) = \begin{cases} 0, w_i = w_j \\ 1, else \end{cases} \tag{7}$$

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

### 4.2. New Style Calligraphy Character Synthesis

Radical selection. 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, 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 $R_t = \left(c_t, p_t, rw_t, v_t, w_t\right)$, the matching degree calculation formula is:

$$M_R = \lambda_1 RC\left(c_t, c\right) + \lambda_2 RP\left(p_t, p\right) + \lambda_3 RW\left(rw_t, W_f\right) + \lambda_4 RV\left(v_t, v\right) + \lambda_5 RG\left(w_t, w_f\right) \tag{8}$$

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:

ISSN: 2472-3703 DOI: 10.6911/WSRJ.202105_7(5).0048

$$\begin{cases} RC(c_t, c) = |c_t - c|, \\ RP(p_t, p) = \sqrt{(p_t - p)(p_t - p)^T}, \\ RW(rw_t, W_f) = |rw_t - W_f|, \\ RV(v_t, v) = |v_t - v|, \\ RG(w_i, w_j) = \begin{cases} 0, w_t = w_f \\ 1, else \end{cases}. \end{cases} \tag{9}$$

Character synthesis. After the corresponding radicals are obtained, they are synthesized according to the position of the reference standard font radicals. Assuming that there are $n$ radicals in calligraphy characters, $r_i$ and $r_j$ are two adjacent radicals. The distance between them in the standard font is $d_s$, and the distance $d_r$ in the synthesized character should satisfy:

$$0 \le d_r \le d_s \tag{10}$$

## 4.3. New Style Calligraphy Character Radical Synthesis

Stroke selection. When there are no radicals that make up calligraphy characters in the radical database, the radicals are decomposed into 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 $S = (b, q, sv, sp)$, the target stroke feature vector is $S^{'} = (b^{'}, q^{'}, sv^{'}, sp^{'}, sw)$, the average stroke width of the work where the target style reference character in is $\overline{W_f}$, and the measurement formula is:

$$M_s = \omega_1 B(b, b^{'}) + \omega_2 Q(q, q^{'}) + \omega_3 SV(sv, sv^{'}) + \omega_4 SP(sp, sp^{'}) + \omega_5 SW(sw, \overline{W_f}) \tag{11}$$

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

$$\begin{cases} B(b, b^{'}) = |b - b^{'}|, \\ Q(q, q^{'}) = |q - q^{'}|, \\ SV(sv, sv^{'}) = |sv - sv^{'}|, \\ SP(sp, sp^{'}) = \sqrt{(sp_x - sp_x^{'})^2 + (sp_y - sp_y^{'})^2}, \\ SW(sw, \overline{W_f}) = |sw - \overline{W_f}|. \end{cases} \tag{12}$$

World Scientific Research Journal Volume 7 Issue 5, 2021
ISSN: 2472-3703 DOI: 10.6911/WSRJ.202105_7(5).0048

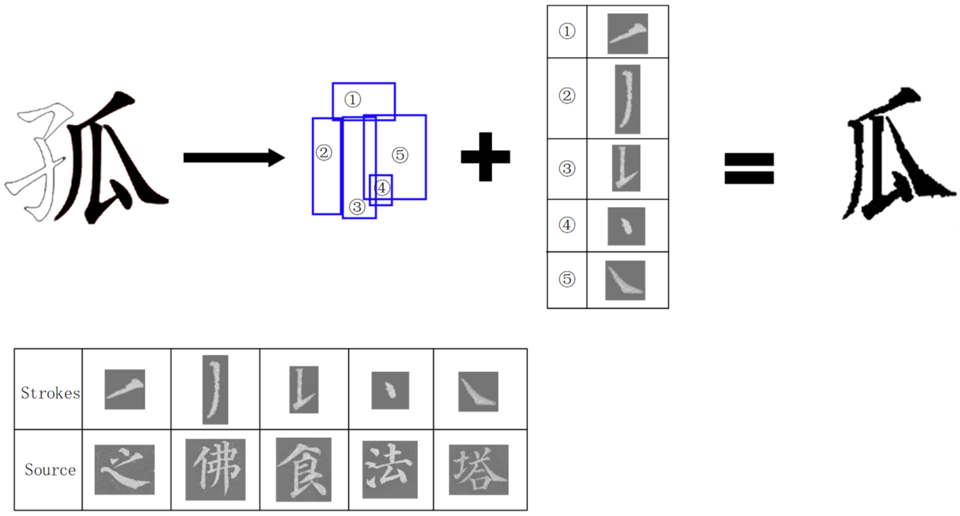


**Figure 3.** Progress of radical synthesis

Radical synthesis. Strokes synthesis radicals need to know the position and size of the strokes in the radicals. Our method uses standard font that style similar to the target style as a reference to synthesize radicals. Figure 3 shows the progress of radical synthesis, first obtain the character from the standard font file, and then obtain the position of the radical 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. After that, the radicals are synthesized into complete calligraphy characters according to the radical synthesis method.

## 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 centroid of a column of characters on a straight line. Suppose the abscissa $H_{ref}$ of the centroid of the first character in each line of the generated work be the baseline, the adjusted abscissa of the centroid 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:

$$\left|G_{nx} - H_{ref}\right| \le \varepsilon \tag{13}$$

$$\left|D'_{nrow} - D'_{row}\right| \le \sigma_r \tag{14}$$

$$\left|D'_{ncol} - D'_{col}\right| \le \sigma_c \tag{15}$$

Where $\varepsilon$ is constant, $\sigma_r$ and $\sigma_c$ are the standard deviations of the row-column distance of the target style respectively. In fact, the centroid of the characters in each line does not need to be on a straight line, it can deviate slightly (inequality 13). The row and column distance of the generated works should be similar to the target style (inequality 14 and inequality 15).

World Scientific Research Journal Volume 7 Issue 5, 2021
ISSN: 2472-3703 DOI: 10.6911/WSRJ.202105_7(5).0048

## 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), and it belongs to font Kaiti, so standard Kaiti is used as a reference font. The database calligraphy style based on 1389 images of Yan zhenqing's calligraphy characters.


**Figure 4.** Character synthesis

In this experiment, a specific style conversion of calligraphy characters was realized, and calligraphy works of a specific style were generated. First, decompose the radicals of the calligraphy characters that are not in the database (Figure 4a and Figure 4b); then match the optimal target style radicals from the database according to the radicals (Figure 4c); finally, combine the radicals to synthesize the calligraphy characters (Figure 4d). If the corresponding radical does not exist in the database, the radicals are decomposed into strokes, and the radicals are synthesized according to the method in section 4.3. The synthesized calligraphy characters in Figure 5 are calligraphy characters that are not in the database.

**Figure 5.** Character synthesis result

The system finally arranges the generated calligraphy characters to generate a work. The Figure 6 the style transfer of calligraphers Lu Zhongnan (Figure 6a) and Zhao Mengfu(Figure 6c), the target style is Yan Zhenqing's style(Figure 6e).

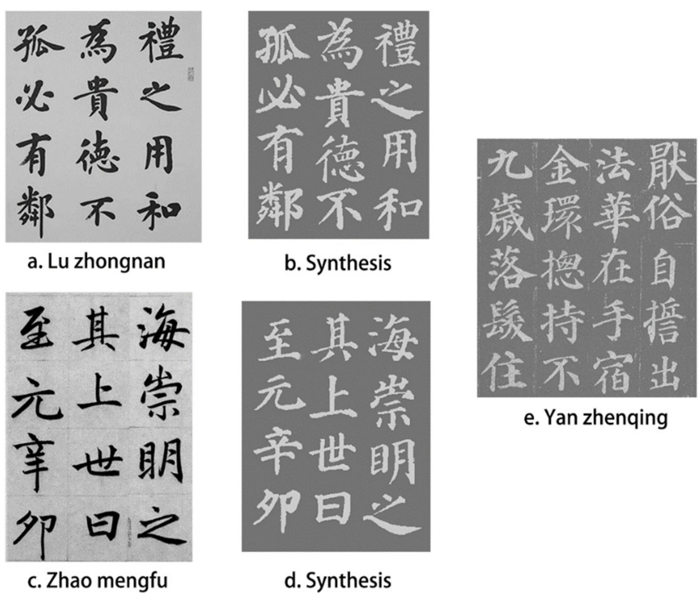


**Figure 6.** Calligraphy work synthesis

ISSN: 2472-3703 DOI: 10.6911/WSRJ.202105_7(5).0048

## 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.

## REFERENCES

[1] Wong H T F, Ip H H S. Virtual brush: a model-based synthesis of Chinese calligraphy[J]. Computers & Graphics, 2000, 24(1): 99-113.

[2] Xu S, Tang M, Lau F, et al. A solid model based virtual hairy brush[C]//Computer Graphics Forum. Oxford, UK: Blackwell Publishing, Inc, 2002, 21(3): 299-308.

[3] Wu Y, Zhuang Y, Pan Y, et al. Web based chinese calligraphy learning with 3-d visualization method[C]//2006 IEEE International Conference on Multimedia and Expo. IEEE, 2006: 2073-2076.

[4] Yu K, Wu J, Zhuang Y. Style-consistency calligraphy synthesis system in digital library[C]//Proceedings of the 9th ACM/IEEE-CS joint conference on Digital libraries. 2009: 145-152.

[5] Zhang J, Mao G, Lin H, et al. Outline font generating from images of ancient Chinese calligraphy[M]//Transactions on edutainment V. Springer, Berlin, Heidelberg, 2011: 122-131.

[6] Velek O, Liu C L, Nakagawa M. Generating realistic kanji character images from on-line patterns[C]//Proceedings of Sixth International Conference on Document Analysis and Recognition. IEEE,2001: 556-560.

[7] Shi C, Xiao J, Jia W, et al. Character feature integration of Chinese calligraphy and font[C]//Document Recognition and Retrieval XX. International Society for Optics and Photonics, 2013, 8658: 86580M.

[8] Tian, Y. 2016. Rewrite: Neural style transfer for Chines fonts. https://github.com/-kaonashi-tyc/Rewrite.

[9] Tian, Y. 2017. zi2zi: Master chinese calligraphy with conditional adversarial net- works. https://github.com/kaonashi-tyc/zi2zi.

[10] Jiang Y, Lian Z, Tang Y, et al. SCFont: Structure-Guided Chinese Font Generation via Deep Stacked Networks[C]//Proceedings of the AAAI Conference on Artificial Intelligence. 2019, 33: 4015-4022.

[11] Gao Y, Guo Y, Lian Z, et al. Artistic glyph image synthesis via one-stage few-shot learning[J]. ACM Transactions on Graphics (TOG), 2019, 38(6): 1-12.

[12] Li Jin, Gao Jing, Chen Junjie, Wang Yongjun. Mongolian font style transfer model based on conditional generation confrontation network[J]. Chinese Information Journal,2020,34(04):55-59+68.

[13] Azadi S, Fisher M, Kim V G, et al. Multi-content gan for few-shot font style transfer[C]//Proceedings of the IEEE conference on computer vision and pattern recognition. 2018: 7564-7573.