# Character Feature Integration of Chinese Calligraphy and Font

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## ABSTRACT

A framework is proposed in this paper to effectively generate a new hybrid character type by means of integrating local contour feature of Chinese calligraphy with structural feature of font in computer system. To explore traditional art manifestation of calligraphy, multi-directional spatial filter is applied for local contour feature extraction. Then the contour of character image is divided into sub-images. The sub-images in the identical position from various characters are estimated by Gaussian distribution. According to its probability distribution, the dilation operator and erosion operator are designed to adjust the boundary of font image. And then new Chinese character images are generated which possess both contour feature of artistical calligraphy and elaborate structural feature of font. Experimental results demonstrate the new characters are visually acceptable, and the proposed framework is an effective and efficient strategy to automatically generate the new hybrid character of calligraphy and font.

**Keywords:** Chinese calligraphy, font, character feature, integration

## 1. INTRODUCTION

Chinese character takes a dual role of information transmission in modern age and traditional art manifestation from historical perspective. It is significant to explore glyph, which influences human cognition and vision in daily life, utilizing advanced modern digital algorithms. There are two kinds of orgnizations have strong interest in glyph: font manufacturers and groups of computer art researchers. Font manufacturers master mature technologies to manually design elegant glyph of font[1-3]. Whereas, computer scientists devote to automatically generate Chinese calligraphy[4-7]. In order to speed up generation of Chinese character, much research has been made on automatic imitation of Chinese calligraphy. In general, the algorithms to automatically generate Chinese character can be broadly classified into two categories: strokes and radicals reused algorithm (SRRA)[7, 9-11] and stroke order drawing algorithm (SODA)[4, 6, 8, 12-14]. SRRA inherits the idea from the production of font that reused strokes and radicals are employed to construct Chinese character. On the contrary, SODA draws character according to stroke order of handwriting.

Two features of glyph: contour and skeleton, are often investigated by font manufacturers and computer researchers. Contour of glyph reflects style of stroke shape, and skeleton reveals structural information of character. The production process of font and SRRA firstly design basic strokes which to a large extent determines the contour feature of glyph, and then construct character with reused strokes and radicals to form the structure of glyph. However SODA first builds structural feature: skeleton, and then draw strokes along skeleton according to stroke order. This work also considers contour feature and structural feature of glyph, and a framework is proposed to yield new hybrid character obtaining artistic contour feature from calligraphy and elaborate structural feature of font.

The procedure of the proposed feature integration framework, as shown in Figure 1, includes four steps: Contour Extraction, Spatial Filtering, Distribution Estimation, and Integration. In section 2, previous work on SRRA and SODA is introduced. Section 3 takes an overview of the proposed framework integrating local contour feature of calligraphy with structural feature of font. The spatial filtering and distribution estimation strategies are proposed in section 4, to extract local contour feature from Chinese calligraphy character. Section 5 presents the algorithm of integrating contour feature from calligraphy with structural feature to generate a hybrid Chinese character. The experimental results and discussion are in section 6. The conclusion is given in last section.

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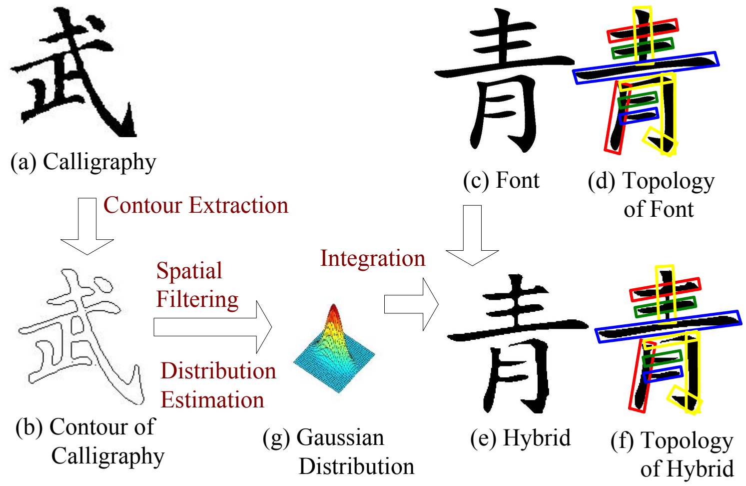


Figure 1. The proposed framework integrating local contour feature of calligraphy with structural feature of font.

## 2. PREVIOUS WORK

In this section, the state of art on SRRA and SODA is introduced. Related work on feature extraction from glyph is reviewed, which is the critical preprocess for SODA to calculate drawing parameters from contour feature and skeleton feature.

In general, SRRA exploit existing strokes and radicals to iteratively multiply characters. Lai et al.[9, 10] analyze the hierarchical relationships between strokes and radicals, and propose a structural expression for Chinese character. Based on the expression and glyph beauty metrics from traditional Chinese calligraphy, glyph is generated automatically. To further consider contour feature of strokes, Xu et al.[7, 11] categorize features representing calligraphic style into two parts: the stroke feature which depicts local style and the geometry topology describing global structural feature of an individual Chinese character. Considering both local and global features, Shi et al.[21] propose an automatic generation algorithm of Chinese character based on human vision and prior knowledge of calligraphy.

To imitate the handwriting process, SODA draws character according to stroke order. Before the imitation, the critical preprocess is to calculate drawing parameters from contour and skeleton of glyph, such as Wong et al.[15] exploring structural feature and drawing parameters through configured ellipse, Yu et al.[16] proposing a skeleton extraction algorithm for Chinese calligraphy, Zhuang et al.[17] investigating Gabor feature from calligraphy, and Xu et al.[18] extracting contour feature with weighted mask walking along contour of glyph. The character generation process is to draw stroke along skeleton according to stroke order. A natural and intuitive strategy is to build mathematical models for Chinese hairy brush. Mi et al.[5, 19] propose a virtual brush model and droplet operation to generate Chinese calligraphy. For further analyzing deformation of brush, Bai et al.[4, 12] present brush geometry model and brush dynamic model to automatically generate of Chinese calligraphy or painting. As a result of reducing computational complexity caused by solid model of physical brush, Yao et al.[8] utilize B-Spline and mechanical parameter to draw calligraphy. Employing a more robust parametric representation of stroke trajectories, Xu et al.[20] draw elegant calligraphy character by using supervised machine learning algorithm. Based on inherent geometric features and prior knowledge of given characters, Yang and Li[6] use parameterized strokes to animate Chinese characters. A great number of works on SODA is proposed to reproduce Chinese handwriting.

## 3. OVERVIEW OF INTEGRATION FRAMEWORK

As is shown in Figure 1, the procedure of the proposed feature integration framework includes four steps: Contour Extraction, Spatial Filtering, Distribution Estimation, and Combination. To evaluate the proposed framework, a data set containing 320 Chinese calligraphy characters was collected in Table 1, which includes works of four calligraphists: Yan Zhenqing (Tang Dynasty, A.D. 709-785), Huang Tingjian (Song Dynasty, A.D. 1045-1105), Kang Youwei (Qing

Dynasty, A.D. 1858-1927) and Liang Qichao (Qing Dynasty, A.D. 1873-1929), 80 characters per person. As can be seen from Table 1, contour styles from four sample characters of the same Chinese character "of" are obviously distinguishable. In the step of Contour Extraction, the contour of calligraphy was obtained by utilizing Canny edge detector. Contour (Figure 1(b)) is extracted from Chinese calligraphy character (Figure 1(a)).

A preprocessing in Spatial Filtering step is to divide the $a$ th calligraphist's $i$ th character contour image into $R \times C$ sub-images, here $a = 1,2,3,4$ and $i = 1,2,3,...,80$ . Each sub-image is filtered by a group of line detectors.

$$R_{a,i,r,c,\theta} = SFilter\left(SubCI_{a,i,r,c}, L_{\theta,s}\right) \tag{1}$$

where $SubCI_{a,i,r,c}$ is a sub-image of contour at location $(r,c)$ from the $a$ th calligraphist's $i$ th character, $L_{\theta,s}$ is line detector with anticlockwise angle $\theta$ and size of $s \times s$ , and $R_{a,i,r,c,\theta}$ is the response of $SubCI_{r,c}$ after spatial filtering with $L_{\theta,s}$ , here, $r = 1,2,...,R$ ; $c = 1,2,...,C$ .

The task of Distribution Estimation step is to estimate probability distribution of $R_{r,c}$ with Gaussian function for each calligraphist, which represents local contour feature of calligraphy. Figure 1(g) visualizes a Gaussian distribution. And this extracted local contour feature will be integrated with structural feature in Integration step. Note that colour boxes in Figure 1(d) bound strokes, and the layout of colour boxes illustrates topology of font. Intuitively, Figure 1(f) shows almost the same topology corresponding to Figure 1(d). On the other hand, the contour changed obviously by comparing Figure 1(c) and Figure 1(e). The hybrid in Figure 1(e) possesses the contour style of calligraphy and the topology of font. More great details are given as following sections.

Table 1. Chinese calligraphy set.

| Calligraphist | Yan Zhenqing | Huang Tingjian | Kang Youwei | Liang Qichao |
|---|---|---|---|---|
| Dynasty | Tang<br>A.D.709–785 | Song<br>A.D.1045–1105 | Qing<br>A.D.1858–1927 | Qing<br>A.D.1873–1929 |
| Sample |  |  |  |  |

# 4. DISTRIBUTION ESTIMATION OF CALLIGRAPHY CONTOUR

In this section, the probability distribution of slopes of all $R_{a,i,r,c,\theta}$ at particular location $(r,c)$ of each calligraphist is estimated using Gaussian function:

$$G(x)_{a,r,c,\theta} = \frac{1}{\left(2\pi\delta^2\right)^{1/2}} \exp\left\{-\frac{1}{2\delta^2}(x-\mu)^2\right\} \tag{2}$$

which is employed to describe the local contour feature of the $a$ th calligraphist's characters. In fact, $R_{a,i,r,c,\theta}$ is possible to contains more than one line (curve) or a cross line, and the effective area may be too small (e.g. a dot). This sort of phenomena leads to multi-value and invalid value of slope. To solve this problem, a area threshold operator and an endpoint detection operator are applied to $R_{a,i,r,c,\theta}$ :

$$AT\left(R_{a,i,r,c,\theta}, T\right) = \begin{cases} R_{a,i,r,c,\theta}, & EA\left(R_{a,i,r,c,\theta}\right) \geq T \\ Null, & EA\left(R_{a,i,r,c,\theta}\right) < T \end{cases} \tag{3}$$

where $EA\left(R_{a,i,r,c,\theta}\right)$ is to calculate the effective area of $R_{a,i,r,c,\theta}$ , and $AT\left(R_{a,i,r,c,\theta}, T\right)$ is the area threshold function. If the effective area of $R_{a,i,r,c,\theta}$ is greater than or equal to the given threshold T, $AT\left(R_{a,i,r,c,\theta}, T\right)$ returns $R_{a,i,r,c,\theta}$ , otherwise $R_{a,i,r,c,\theta}$ is discarded. And then each remained $R_{a,i,r,c,\theta}$ is operated upon by the endpoint detection operator:

$$EPD\left(R_{a,i,r,c,\theta}\right)=\begin{cases}\left[ep_1\ ep_2\right]^T, & NEP\left(R_{a,i,r,c,\theta}\right)=2\\ Null, & NEP\left(R_{a,i,r,c,\theta}\right)\neq 2\end{cases} \tag{4}$$

where $NEP\left(R_{a,i,r,c,\theta}\right)$ returns the number of endpoints in $R_{a,i,r,c,\theta}$, and if $NEP\left(R_{a,i,r,c,\theta}\right)=2$ the endpoint detection function $EPD\left(R_{a,i,r,c,\theta}\right)$ gives a column vector $\left[ep_1\ ep_2\right]^T$, from which the slope of $\overline{ep_1 ep_2}$ can be gained: $x_{a,i,r,c,\theta}$, of which the probability distribution is estimated by (2).

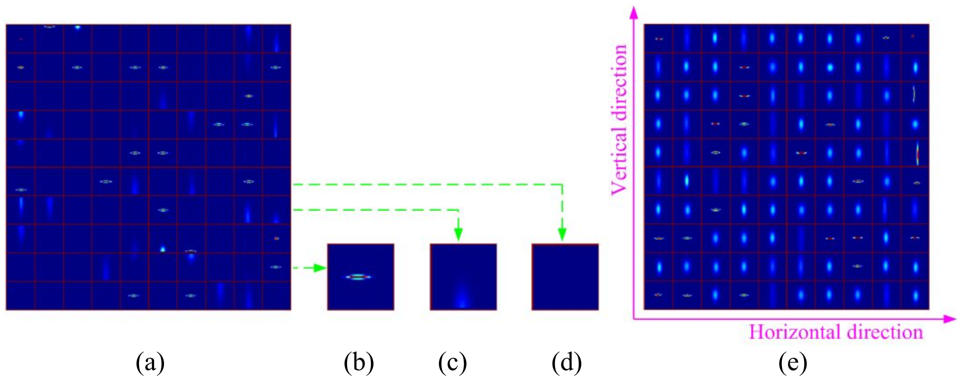


Figure 2. Visualization of local contour feature from two calligraphists: (a) contour feature of Yan Zhenqing's 80 calligraphy characters in 10×10 grids; (b) the grid at row 9 and column 10 of the 10×10 grids in (a); (c) the grid at row 7 and column 10 of the 10×10 grids in (a); (d) the grid at row 6 and column 10 of the 10×10 grids in (a); (e) contour feature of Liang Qichao's 80 calligraphy characters in 10×10 grids with horizontal arrow and vertical arrow.

To further give an intuitive visualization of defined local contour feature in (2), Yan Zhenqing's 80 calligraphy characters and Liang Qichao's 80 calligraphy characters, as described in Table 1, were used to calculate parameters for (2). Each character image was divided into $10\times10$ sub-images, $\theta\in\{0,\pi/2\}$ and $s=5\,pixels$ in (1), and $T=5\,pixels$ in (3). The mean values and standard deviations corresponding to differing $\theta$ are combined to:

$$G(\mathbf{x})_{a,r,c,(\theta_1,\theta_2)}=\frac{1}{2\pi\left(\Sigma\right)^{1/2}}\exp\left\{-\frac{1}{2}\left(\mathbf{x}-\boldsymbol{\mu}\right)^T\Sigma^{-1}\left(\mathbf{x}-\boldsymbol{\mu}\right)\right\} \tag{5}$$

where $\mathbf{x}=\left[x_{a,i,r,c,\theta_1},x_{a,i,r,c,\theta_2}\right]^T$, $\boldsymbol{\mu}=\left[\mu_{a,r,c,\theta_1},\mu_{a,r,c,\theta_2}\right]^T$, and:

$$\Sigma=\begin{bmatrix}\delta_{a,r,c,\theta_1} & \mathbf{0}\\ \mathbf{0} & \delta_{a,r,c,\theta_2}\end{bmatrix} \tag{6}$$

Figure 2(a) and (e) show the visualization of $10\times10$ grids of local contour feature for two calligraphists: Yan Zhenqing and Liang Qichao. As described in (5), for each calligraphist, $r=1,2,...,10$, $c=1,2,...,10$, $\theta_1=0$, $\theta_2=\pi/2$. Two angles are indicated by two arrows in Figure 2(e). In each grid, the bright spot illustrates 2D Gaussian distribution in (5). The center of the bright spot is determined by $\boldsymbol{\mu}$, and the approximate elliptical shape of the bright spot is controlled by $\Sigma$. Obviously, an interesting phenomenon is the number of bright spots in Figure 2(e) is much larger than it in Figure 4(a). Three grids of Figure 4(a) are analyzed to explore underlying reasons. As shown in Figure 4(b)~(d), the shape of the bright spot in Figure 4(b) implies $\delta_{a_1,9,10,0}>\delta_{a_2,9,10,\pi/2}$, in other words, the long axis of the ellipse is along the horizontal direction. The long tail by vertical direction of the bright spot in Figure 4(c) indicates the center of the bright spot is out of the coordinate system in the grid at location $(7,10)$. Empty is shown in the grid at location $(6,10)$, and there are two conditions: firstly, the bright spot is totally out of the coordinate system in the grid; secondly, a area threshold operator and an endpoint detection operator are applied to $R_{a,i,r,c,\theta}$ so that the output of (4) is $Null$. The above analysis explains why Figure 2(e) looks more sparkling than Figure 2(a), and the noticeable disparity of visual effect infers the unique local contour feature of each calligraphist.

## 5. FEATURE INTEGRATION OF CALLIGRAPHY WITH FONT

The local contour feature defined in formula (2) is integrated with structural feature of font in this section. As previously described, font has elaborate structure, hence, naturally a simple and effective integration strategy is proposed to adjust contour of font according to the definition of local contour feature in (2). A font image is divided into $R \times C$ sub-images so as to sub-image of font at location $(r,c)$ can be adjusted using $G(x)_{a,r,c,\theta}$ as described in (2). In fact, the parameter $a$ depends on which calligraphist's local contour feature will be exploited, and only one parameter of $G(x)_{a,r,c,\theta}$ is TBD: $\theta$.

To choose the parameter $\theta$, the sub-image of font $SubF_{r,c}$ is filtered by a group of line detectors, similar to (1).

$$R'_{r,c,\theta} = SFilter\left(SubF_{r,c}, L_{\theta,s}\right) \tag{7}$$

and then, the best $\theta$ is obtained according to:

$$\theta = \underset{\theta \in \{\theta_1,\theta_2,\ldots,\theta_k\}}{\arg\max} \left\{R'_{r,c,\theta}\right\} \tag{8}$$

Finally, parameters $\mu$ and $\delta$ in (2) are estimated. A slope can be generated according to:

$$x = \mu + k\delta \tag{9}$$

where $k$ is a adjustable parameter. A dilation operator is designed as:

$$L_{\tan^{-1}(x),s} \tag{10}$$

where $\tan^{-1}(\cdot)$ is the inverse tangent. Two erosion operators are defined:

$$EMask_1 = \begin{bmatrix} 0 & 1 & 0 \\ 1 & 1 & 1 \\ 0 & 1 & 0 \end{bmatrix} \qquad EMask_2 = \begin{bmatrix} 1 & 0 & 1 \\ 0 & 1 & 0 \\ 1 & 0 & 1 \end{bmatrix} \tag{11}$$

The dilation operator and the erosion operator ($EMask_1$ or $EMask_2$) are iteratively executed to adjust boundary of font. The adjustment process can be seen as a sculpture progress. The dilation integrates local contour feature of calligraphy with structural feature of font using "pad", whereas, erosion acts as a "graver" to "cut" contour of font.

## 6. EXPERIMENT AND ANALYSIS

To evaluate the proposed integration framework, a data set containing 320 Chinese calligraphy characters was collected in Table 1. Experiments integrated calligraphy from four calligraphists with "Li Shu" font and "Kai Ti" font. And the setup is as follows: in formula (1), $a = 1,2,3,4$ corresponds to four calligraphists, $i = 1,2,3,\ldots,80$ is the iterator of calligraphy character for each calligraphist, contour image of each calligraphy character is divided into $10 \times 10$ sub-images, the size of the line detector $L_{\theta,s}$ is $5 \times 5$, and $\theta = 0, \pi/2, \pi/4, -\pi/4$. The area threshold $T = 5$ in (3). The local contour feature for each calligraphist can be gained using formula (2). In the integration process, font image is also divided into $10 \times 10$ sub-images, $s = 5$ and $\theta = 0, \pi/2, \pi/4, -\pi/4$ in (7), dilation operator $EMask_1$ is selected in (11), and $k = 0$ in (9).

Figure 3 shows the poem "Duan Ge Xing" of a famous poet Cao Cao in acient China, which contains 128 characters. Figure 3(a) shows 64 hybrids integrating Liang Qichao's calligraphy character with "Kai Ti" font, and the rest of 64 hybrids integrating Yan Zhenqing's calligraphy character with "Li Shu" font are exhibited in Figure 3(b). "KT-Hybrid" and "LS-Hybrid" are used as abbreviations of the two sorts of hybrids. In general, KT-Hybrid and LS-Hybrid maintain both the structural style from font and the contour style from calligraphy character. In particular, two kinds of Chinese calligraphy skills are imitated in KT-Hybrid and LS-Hybrid: one is called "Fei Bai", and the other is named "Zhang Mo". "Fei Bai" depicts a phenomenon that part of a stroke fade out due to the fast movement of hair brush or the lack of ink. "Zhang Mo" describes a condition that hair brush holds so much ink that strokes overlap. Four KT-Hybrid characters and four LS-Hybrid characters are picked out from Figure 3 to illustrate the artistic effect caused by "Fei Bai" and "Zhang Mo" in Figure 4. When comparing KT-Hybrid in Figure 4(a) and "Kai Ti" in Figure 4(c), the fadeout of some Horizontal strokes occurs in four KT-Hybrid characters. The principled rason resulting in fadeout of strokes is $\tan^{-1}(x)=0$ in (10), in other words, $L_{\tan^{-1}(x),s}$ is a horizontal line. The more intuitive explanation is that $L_{0,s}$ "pads" Horizontal strokes with nothing and $EMask_1$ cuts them too much. The impact of calligraphy skill "Zhan Nian" is obvious through comparison between Figure 4(b) and (d). It is contrary to "Fei Bai", "Zhang Mo" employs dilation operator to "pad" strokes so much that it seems too much ink drops down from hair brush to let strokes overlap each other.

To further investigate the visual acceptance of KT-Hybrid and LS-Hybrid, a mixed character dataset was built including eight classes: Yan Zhenqing, Huang Tingjian, Kang Youwei, Liang Qichao, "Kai Ti" font, "Li Shu" font, KT-Hybrid, LS-Hybrid. The first four classes belong to Chinese calligraphy, the fifth and the sixth are fonts, and the last two are hybrids created by the proposed integration framework. 40 characters per each class, totally 320 characters are disordered randomly. 25 people were invited to pick characters which they thought are visually unacceptable on the aspect of aesthetics of Chinese character. The number of picked characters is unlimited. The result of picking is visualized in Figure 5. Horizontal axis and vertical axis represent the number of character and the number of invited people, respectively. $25\times320$ grids illustrate which character is picked by whom. If a character is picked by someone, the grid on the cross of the character and the people is black. As can be seen from the grids, all picked grids don't cluster in only one intensive area, and they scatter randomly. It is safe to conclude the two hybrids are visually acceptable, relative to font. Three relatively intensive picking areas are numbered. The area numbered "1" indicates the seventh people recognized almost all Kang Youwei's calligraphy characters. The two areas numbered with "2" and "3" imply the sixth people recognized all "Kai Ti" fonts and Most KT-Hybrid characters. In fact, KT-Hybrid has the structural feature from "Kai Ti" font. This phenomon infers the proposed framework successfully integrate Chinese calligraphy character and font.

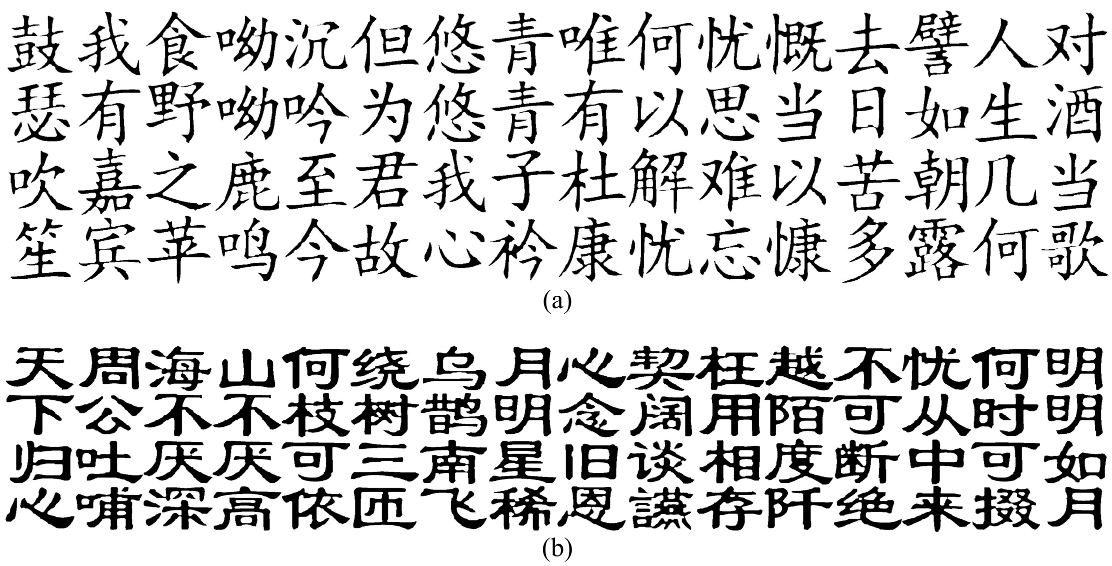


Figure 3. The poem "Duan Ge Xing" of Cao Cao (a famous poet and politician in acient China, A.D. 155–220): (a) the first half part of the poem, hybrid of contour feature of Liang Qichao's calligraphy and structural feature of "Kai Ti" font; (b) the second half part of the poem, hybrid of contour feature of Yan Zhenqing's calligraphy and structural feature of "Li Shu" font.

Figure 4. Comparison between hybrid and font: (a) four KT-Hybrid characters; (b) four LS-Hybrid characters; (c) four “Kai Ti” fonts; (d) four “Li Shu” fonts.

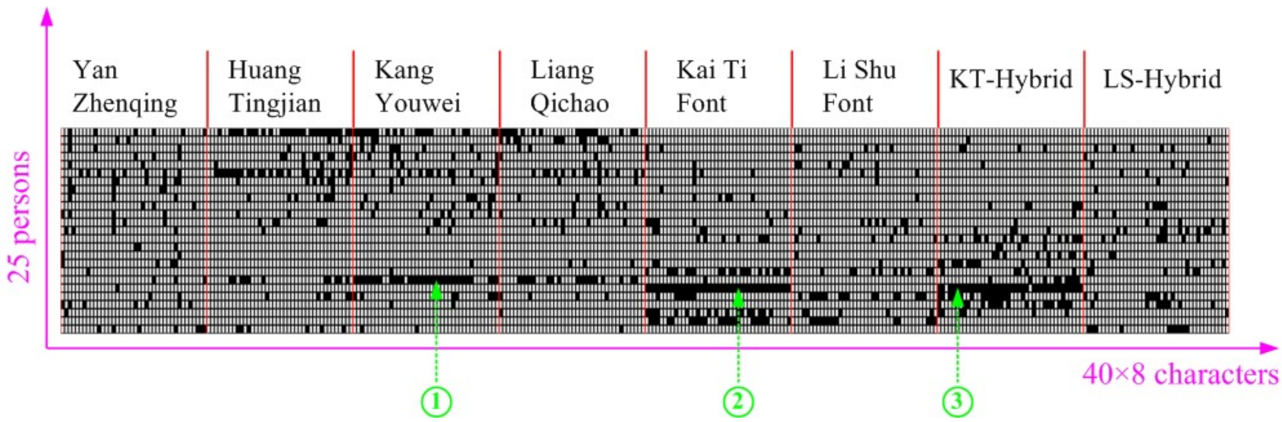

Figure 5. Visualization of picking results. 25×(40×8) grids are used to illustrate who picks which characters. The grid, which is on the cross of picked character and people who picks, is labeled with black, otherwise it’s white. 7 vertical lines divide 8 classes, of which each class contains 40 characters. Three numbers label relatively intensive picking areas.

## 7. CONCLUSION

In this work, a framework is proposed to integrate local contour feature of Chinese calligraphy characters and structural feature of font. The local contour feature is defined by Gaussian function, which reflects slope distribution in sub-images of calligraphy characters. The visualization of the local contour feature proves each calligraphist has his own contour style from a statistical perspective. In integration process, a dilation operator is generated according to the local contour feature of a particular calligraphist, which is used with an erosion operator to adjust boundary of font. Finally a hybrid of a calligraphist’s calligraphy and font is created by the proposed integration framework. The experimental results demonstrate the created hybrids are visually acceptable, which maintains local contour feature of calligraphy character and elaborate structural feature of font. The proposed framework provides an effective and efficient methodology to generate Chinese character which can be used for digital entertainment in cyberspace and 3G mobile network, in order to improve user experience.

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