Automatic Generation of Chinese Character Based on Human Vision and Prior Knowledge of Calligraphy

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Abstract. Prior knowledge of Chinese calligraphy is modeled in this paper, and the hierarchical relationship of strokes and radicals is represented by a novel five layer framework. Calligraphist's unique calligraphy skill is analyzed and his particular strokes, radicals and layout patterns provide raw element for the proposed five layers. The criteria of visual aesthetics based on Marr's vision assumption are built for the proposed algorithm of automatic generation of Chinese character. The Bayesian statistics is introduced to characterize the character generation process as a Bayesian dynamic model, in which, parameters to translate, rotate and scale strokes, radicals are controlled by the state equation, as well as the proposed visual aesthetics is employed by the measurement equation. Experimental results show the automatically generated characters have almost the same visual acceptance compared to calligraphist's artwork.

Keywords: Chinese character, automatic generation, human vision, prior knowledge of calligraphy, Bayesian statistics.

1 Introduction

The automatic generation of Chinese character attracts researchers' attention[1-7]. It is significant to explore underlying principles on Chinese character glyph in various aspects. Chinese script, which has evolved along with change of society and culture, transmitted information in daily life and provided aesthetic perception in art. Its geometrical shape in particular historical period implied Calligraphic trend and distinctive civilization feature. Moreover, a calligraphist's unique handwriting skills infer his own emotion and experience. This paper employs visual aesthetics and prior knowledge of calligraphy to generate Chinese character.

Two types of organizations paid most attention on Chinese glyph: font companies[8-11] and Chinese character research groups. Font companies must supply sufficient new fonts to China media market in time. The new fonts need to match the commercial requirements as well as satisfy the Chinese government standard, such as GB2312, GBK and GB13000.1 etc. These companies employ a large amount of glyph designers and workers to manufacture elaborate Chinese font. The production process

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of font is time-consuming and costly. During the whole process, firstly, basic strokes of originality are created by font designer to decide stroke style of the new font. Secondly, radicals are composed of the created strokes. Finally, radicals construct Chinese characters. The three steps are logical. In fact, the production process is dynamic and iterative, in other words, the design of stroke, the composition and the decomposition of radicals or characters are iterative so that the number of characters increases gradually and dynamically.

In order to speed up font manufacture and realize calligraphic manifestation using information technology, innovative models[1-6, 12] and systems[7, 13-15] were proposed to automatically generate Chinese character. In general, methodologies broadly exploit two categories of ideas: imitating handwriting procedure[1-3, 6, 13, 16] and composing new characters with samples[4, 5, 17, 18]. Being different from previous work, this paper considers automatic generation of Chinese character from a novel perspective on visual aesthetics and prior calligraphic knowledge. One research goal is to provide an effective and efficient way to build a prototype for a new style font. The prototype would assist font designer to make or adjust blueprint immediately avoiding failure of the whole production process. Another goal is to fast generate customized Chinese character for digital entertainment in cyberspace.

The remainder of this paper is organized as follows. In next section, previous work on automatic generation of Chinese character is reviewed. Prior knowledge of calligraphy is modeled in Section 3, which reveals unique individual handwriting pattern. In Section 4, visual aesthetics is investigated, which is applied with the proposed model of calligraphic prior knowledge for a novel algorithm to automatically generate Chinese character. The experiments and discussion are presented in Section 5, and Section 6 concludes this paper.

2 Previous Work

Classical Chinese character generation algorithms are reviewed in this section, as mentioned above, which can be generally classified into two categories: handwriting imitation and samples based character generation. The methodology of handwriting imitation extracts geometric and topological features, on which based strokes are drawn. As a topological feature, skeleton of glyph was extracted by Yu et al.[19], and Zhuang et al.[20] explored orientation of strokes using Gabor filter. On the other hand, contour of glyph is a critical geometric feature. Xu et al.[21] extracted contour feature using a weighted mask which slipped along contour of glyph. Moreover, a heuristic method using configured ellipses along skeleton to represent contour was proposed by Wong et al.[12]. After feature extraction, a natural methodology is to imitate handwriting process. Mi et al.[7, 14] designed a virtual brush to draw calligraphic artwork. Bai et al.[1, 2] proposed more complicated brush geometry and dynamic models to represent deformation of brush. Whereas, in order to reduce computational complexity, Yao et al.[16] applied B-Spline to generate Chinese calligraphy instead of sophisticated brush model. For the automatic generation of more elegant character, Xu et al.[15] presented a robust algorithm drawing calligraphy along stroke trajectories.

The other important methodology is to construct new characters using samples. This partly inherits the idea of font production process. Lai et al.[17, 18] utilized the hierarchical relationship of strokes and radicals to compose Chinese character. To further exploit contour feature of glyph, Xu et al.[4, 5] considered both topology between strokes and shape of stroke, etc.

The strategy of handwriting imitation emphasizes the reconstruction of handwriting progress according to extracted geometric and topological features, such as skeleton and contour. It partly considers prior knowledge of calligraphy: the stroke style and the structure of character, however, this paper considers more on calligraphy training process in which the unique individual handwriting pattern of calligraphist is formed. The sampled based character composition exploits correlation between characters depending on statistics. Nevertheless, the research on this paper exceeds statistical correlation, which takes an attempt that using visual aesthetics to generate Chinese character. A character generation algorithm based on calligraphic prior knowledge and visual aesthetics is proposed in the next two sections.

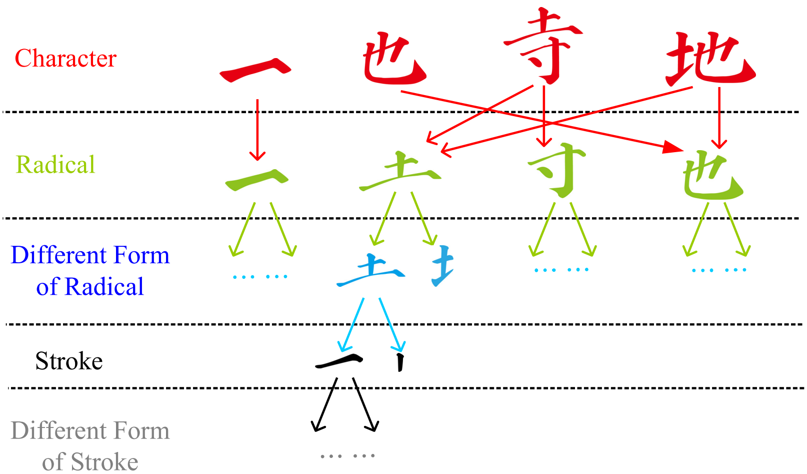

Fig. 1. Five layers framework to represent Chinese character

3 Modeling Prior Knowledge of Calligraphy

In the training process of Chinese calligraphy, a learner practices the sophisticated cooperation between mind and hand. It is always a very long period for a learner and even a whole life for a calligraphist. In this section, the prior knowledge of Chinese calligraphy includes two parts. The first part is the structure of Chinese character, which has been taught to every Chinese pupil for a few years. A five layers framework is proposed in this section to represent the structure of Chinese character, as shown in Fig. 1. The five layers are Character layer (C layer), Radical layer (R layer), Different Form of Radical layer (DFR layer), Stroke layer (S layer), and Different Form of Stroke layer (DFS layer). In the top layer, each element is a Chinese character, which belongs to a layout pattern. Characters "一" and "也" belong to Single-Component layout pattern, "寺" belongs to Top-Bottom layout pattern, and "地" belongs to Left-Right layout pattern. The character "寺" can be decomposed to a top radical "土" and a bottom radical "寸" in R layer. In fact, each radical is a meaning unit which can not be decomposed to smaller radical. However, each radical may have different forms in DFR layer, such as radical "土" has at least two different forms. The two lower layers are S layer and DFS layer. Each element in DFR layer can be decomposed to one or more strokes in S layer, and each stroke may have different forms in DFS layer. The second part of prior knowledge of calligraphy is concerned with calligraphist's unique handwriting skills, on which more details are given in next two sub-sections.

3.1 Modeling Stroke and DFS

Traditionally, a calligraphist practices his unique handwriting skills in whole life, hence the stroke style and layout pattern are stable. As shown in Fig. 2, six characters are written by a calligraphist Yan Zhenqing. The main horizontal lines in each character have big ends on the right, which reveals the calligraphist's handwriting skill: press down the brush hardly at the end of horizontal line. The stable stroke style provides superior samples for DFS layer. A stroke s_i is defined as a set of different forms of the stroke dfs_{ij}:

$$s_i = \{dfs_{ij}\} \quad j = 1, 2, ..., J \tag{1}$$

All six main horizontal lines in different characters shown in Fig. 2 are six different forms strokes of the stroke: horizontal line, here, $J = 6$. An element in DFR layer can be composed from stroke using (2):

$$dfr_{mk} = RCom(rl_k, s_1, s_2, ..., s_n) \tag{2}$$

where different forms of strokes are chosen for strokes $s_1, s_2, ..., s_n$ according to radical layout rl_k, and $RCom(\cdot)$ composes the chosen different forms of strokes to dfr_{mk}, where m indicates the radical r_m.

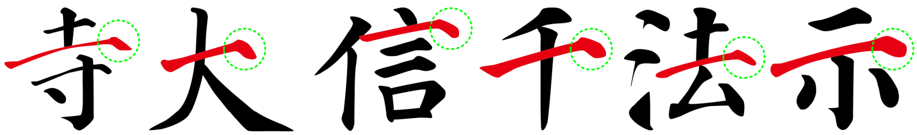

Fig. 2. Six characters written by a famous calligraphist Yan Zhenqing (Tang Dynasty, A.D. 709-785). The right ends of main horizontal lines (red strokes), which are marked with dash circles, indicate the calligraphist's handwriting skill: press down the brush hardly at the end of horizontal line.

3.2 Modeling Radical and DFR

As mentioned in the above sub-section, the layout pattern of a calligraphist's character is stable. As shown in Fig. 3, the same character "感" has two kinds of layout patterns: partially surrounding pattern and top-bottom pattern. In Fig. 3(a)~(c), the radical "心" is partially surrounded by radical "咸", and in Fig. 3(d), the top radical "咸" is just above the bottom radical "心". The core is not concerned with which pattern is correct but which one is your pattern. Hence, the calligraphist's personal layout pattern, as shown in Fig. 3(a)~(b), provides unique layout style for C layer, and also determines rl_k in (2). A character c_p in C layer can be composed by radicals in R layer using (3):

$$c_p = CCom\left(cl_p, r_1, r_2, \ldots, r_m\right) \tag{3}$$

where different forms of radicals are chosen for radicals $r_1, r_2, \ldots, r_m$ according to character layout cl_p, and the character c_p can be composed with the chosen different forms of radicals using $CCom(\cdot)$.

In brief, the structure of Chinese character is modeled using the proposed five layers framework, and the calligraphist's unique handwriting skills provide effective composition strategies for (1)~(3). Two kinds of prior knowledge of calligraphy are made well used to compose Chinese character. An automatic generation algorithm of Chinese character based on visual aesthetics is proposed in next section.

(a) (b) (c) (d)

Fig. 3. The same character with different layout pattern. (a) Yan Zhenqing's character "感"; (b) Yan Zhenqing's character "感" with the same layout pattern of (a); (c) a Kai Ti font "感" with the same layout pattern of (a); (d) another Kai Ti font "感" with a different layout pattern.

4 Automatic Generation Algorithm of Chinese Character

Chinese character can be composed based on prior knowledge of calligraphy using (1) ~ (3). Five layers framework illustrated in Fig. 1 gives a top-down strategy to guide stroke and radical composition. However, formula (2) and (3) only have conceptual solutions. In this section, numerical solutions for (2) and (3) are given using a bottom-top nonlinear and non-Gaussian algorithm based on Marr's vision assumptions[22].

4.1 Modeling Stroke and DFS

The spatial arrangement of objects in an image was investigated by Marr[22] according to a series of physical assumptions. The conclusion of the investigation can be summarized as six points: 1. Average local intensity; 2. Average size of similar objects; 3. Local density of the objects; 4. Local orientation of the objects; 5. Local distances associated with the spatial arrangement of similar objects; 6. Local orientation associated with the spatial arrangement of similar objects. It is inspired from Marr's investigation on spatial arrangement that visual aesthetics is proposed in this subsection.

According to Marr's points 1~3, average stroke intensity and stroke intensity are defined as:

$$\rho_{ij} = Area\left(dfs_{ij}\right) \tag{4}$$

$$\rho'_{mk} = \frac{Area\left(dfr_{mk}\right)}{RNum\left(dfr_{mk}\right)} \tag{5}$$

where $Area(\cdot)$ is the function to calculate area of stroke or radical, and $RNum(\cdot)$ returns the number of strokes in dfr_{mk}. ρ_{ij} is a constant which represents the area of each element in DFS layer. ρ'_{mk} is the ratio of the area of dfr_{mk} to the number of strokes.

The orientation of stroke θ_{ij} and the orientation of radical θ'_{mk} are proposed corresponding to Marr's points 4 and 6. Obviously, it's easy to calculate θ_{ij} of dfs_{ij}. θ'_{mk} is equal to the θ_{ij} of the main stoke in dfr_{mk}. Here, the main stroke of dfr_{mk} is the stroke which has the biggest area among all strokes. The orientation of layout rl_k and cl_p can be represented respectively by:

$$\sum \theta_{ij} - \theta_{i'j'} \tag{6}$$

$$\sum \theta'_{mk} - \theta'_{m'k'} \tag{7}$$

Moreover, the distance between strokes in radical or radicals in character are defined as:

$$\delta_{ij,i'j'} = center\left(dfs_{ij}\right) - center\left(dfs_{i'j'}\right) \tag{8}$$

$$\delta'_{mk,m'k'} = center\left(dfr_{mk}\right) - center\left(dfr_{m'k'}\right) \tag{9}$$

where $center(\cdot)$ calculates the center point of a stroke or a radical. And intersection between strokes and radicals are detected using $Area\left(dfs_{ij} \cap dfs_{i'j'}\right)$ and $Area\left(dfr_{mk} \cap dfr_{m'k'}\right)$. Formula (6)~(9) match Marr's point 5.

As discussed above, rl_k and cl_p are quantified through (4)~(9) inspired by Marr's vision assumption. A nonlinear Bayesian algorithm is proposed in next sub-section to implement (2) and (3).

4.2 Nonlinear Bayesian Algorithm to Generate Character

In order to generate Chinese character satisfying the proposed visual aesthetics, three transformation operators are defined to adjust strokes and radicals described in Fig. 1. The three operators include scaling S, rotation R, and translation T:

$$SRT = \begin{bmatrix} sx & 0 & 0 \\ 0 & sy & 0 \\ 0 & 0 & 1 \end{bmatrix} \cdot \begin{bmatrix} \cos\varphi & -\sin\varphi & 0 \\ \sin\varphi & \cos\varphi & 0 \\ 0 & 0 & 1 \end{bmatrix} \cdot \begin{bmatrix} 1 & 0 & tx \\ 0 & 1 & ty \\ 0 & 0 & 1 \end{bmatrix} \tag{10}$$

The core of character generation is to figure out proper parameters sx, sy, φ, tx, ty, on which depending strokes and radicals are adjusted so that the group of coefficients on visual aesthetics: ρ_{ij}, ρ'_{mk}, $\sum\theta_{ij} - \theta_{i'j'}$, $\sum\theta'_{mk} - \theta'_{m'k'}$, $\delta_{ij,i'j'}$, $\delta'_{mk,m'k'}$, $Area\left(dfs_{ij} \cap dfs_{i'j'}\right)$, and $Area\left(dfr_{mk} \cap dfr_{m'k'}\right)$ etc, satisfy prior knowledge of calligraphy. Obviously, this is an optimal problem.

Firstly, consider the condition that character is composed with two radicals, as described in (3). The Bayesian dynamic models[23] is introduced to solve the optimal problem. The state vector $\mathbf{x}$, $\mathbf{x}'$ and the measurement $\mathbf{z}$ are defined as:

$$\mathbf{x} = \left[sx, sy, \varphi, tx, ty\right]^T \quad \mathbf{x}' = \left[sx', sy', \varphi', tx', ty'\right]^T \tag{11}$$

$$\mathbf{z} = \left[\rho'_{mk}, \sum\theta'_{mk} - \theta'_{m'k'}, \delta'_{mk,m'k'}, Area\left(dfr_{mk} \cap dfr_{m'k'}\right)\right]^T \tag{12}$$

The state equation and the observation equation are:

$$\left[\mathbf{x}_k, \mathbf{x}'_k\right] = f_k\left(\left[\mathbf{x}_{k-1}, \mathbf{x}'_{k-1}\right]\right) \tag{13}$$

$$\mathbf{z}_k = h_k\left(SRT\left(\mathbf{x}_k\right) \cdot HCdfr_{mk}, SRT\left(\mathbf{x}'_k\right) \cdot HCdfr_{m'k'}\right) \tag{14}$$

where $SRT\left(\mathbf{x}_k\right)$ is transformation matrix in (10), and $HCdfr_{mk}$ represents homogeneous coordinates of pixel in dfr_{mk}. Formulae (13) and (14) indicate the states vectors $\mathbf{x}_k$ and $\mathbf{x}'_k$ update along time k until the coefficients on visual aesthetics calculated from two radicals dfr_{mk} $dfr_{m'k'}$ match prior knowledge of calligraphy. The solutions to (13) and (14) are concerned with estimation of probability density function (pdf) using Bayesian theory. Generally, it is hard to figure out analytical solution. Instead, Particle Filter[24], Sequential Importance Sampling (SIS)[25] algorithm, Markov Chain Monte Carlo (MCMC)[26] method, and Sampling Importance Resampling (SIR)[27] filter etc are used to approximate the optimal solution.

The above automatic generation algorithm of Chinese character is concluded as follows:

Step 1: Input prior information of target character and absent radicals.

Step 2: If all radicals to compose the character exist, then turn to Step 4.

Step 3: Compose the absent radicals using the Bayesian dynamic models, similar to (11)~(14).

tep 4: Compose the target character with necessary radicals using the Bayesian dynamic models.

Step 5: Output the target character.

5 Experiments and Discussion

In order to evaluate the proposed algorithm, Yan Zhenqing's 130 calligraphy characters are collected to build a data set. These calligraphy characters are converted into vector graphics and decomposed to radicals and strokes for DFR layer and DFS layer, as illustrated in Fig. 1. The two processes of conversion and decomposition are both executed manually. As shown in Fig. 4, the first row contains ten samples from the calligraphy data set, the second row illustrates vector graphics corresponding to the ten samples in the first row, and the third row demonstrate two radicals and seven strokes of the character "判".

The 14 automatically generated Chinese characters are mixed with Yan Zhenqing's 14 calligraphy characters to quantify the visual acceptance of characters. And 17 persons are invited to pick characters with the worst visual acceptance. The number of picked characters is in the range from 0 to 28. The picking result is visualized in Fig. 5. The horizontal arrow and the vertical arrow indicate characters and invited persons respectively. The black grid represents the picked character as well as the person who picked it. Intuitively, the picked characters are sparse. In fact, the picked probability values of Yan Zhenqing's calligraphy and generated characters are 0.45 and 0.55 respectively. In other words, the proposed algorithm in this paper could generate Chinese characters with almost the same visual acceptance of Yan's calligraphy. To further explore the reason that characters were picked out, five characters are numbered including three calligraphy characters (No.1~3) and two generated characters (No.4~5). Actually, the No.1 character is Yan's calligraphy, and people always subconsciously believe Yan's calligraphy is elegant because of his reputation. The essential reason to pick out No.1 character is that the form of No.1 character in modern age is "玠", of which the right radical is different with Yan's. Hence, the lack of prior knowledge of calligraphy guides people to pick out the No.1 character. The bottom of the No.2 character isn't sealed so well that a hook is exposed. This phenomenon is caused by Yan's handwriting style, which directly lead to the No.4 and No.5 were picked out with the same reason: the exposed hook. As can be seen, the No.3 character and the No.5 character have the same layout pattern "top-bottom", and even the same bottom radical "心". It is a potential reason resulting in that the two characters were picked, whereas, it proves that the proposed algorithm successfully maintains Yan Zhenqing's handwriting style.

In brief, the characters generated by the proposed algorithm get almost the same visual acceptance relative to Yan Zhenqing's calligraphy. The lack of prior knowledge of calligraphy results in contrary visual aesthetics. And the handwriting style of calligraphist can be remained in the generated characters using the proposed algorithm.

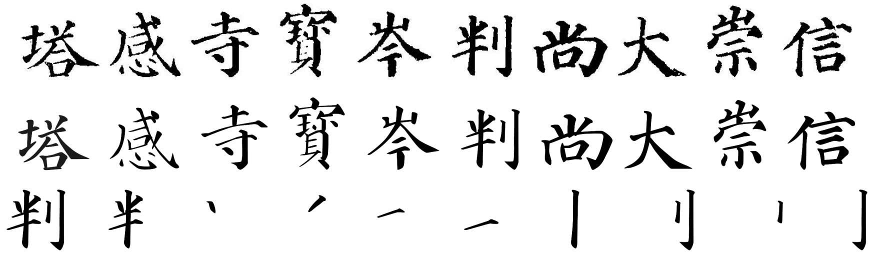

Fig. 4. Ten calligraphy samples, vector graphics and decomposition of character. The first row shows ten samples from the collected Yan Zhenqing's calligraphy data set. The second row illustrates vector graphics corresponding to the first row. And the third row demonstrates two radicals and seven strokes of the character "判".

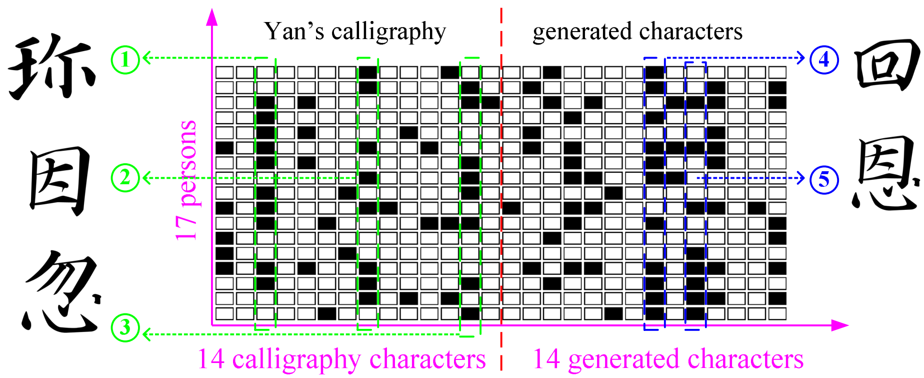

Fig. 5. Visualization of picking results. 17×(14×2) girds are employed to illustrate the visual acceptance of characters. The horizontal arrow and the vertical arrow indicate characters and invited persons respectively. The black grid represents the picked character as well as the person who picked it. The numbered five characters (three calligraphy characters and two generated characters) with high picked probability are showed at two sides.

6 Conclusions

In this paper, prior knowledge of Chinese calligraphy is modeled, and a five layers framework is presented to represent Chinese character. Considering a calligraphist's unique handwriting skills, strokes, radicals and layout pattern are modeled, which provides raw elements for each layer. Marr's vision assumption is deeply analyzed to propose the visual aesthetics for the proposed automatic generation algorithm of Chinese character. The whole generation process can be described as a Bayesian dynamic model, in which, the state equation control the update of parameters to adjust strokes, radicals and their layout, and the proposed visual aesthetics is employed by the measurement equation. Experimental results show the automatically generated characters have almost the same visual acceptance compared to Yan Zhenqing's calligraphy. One reason affecting visual acceptance is the extent of mastering prior knowledge of calligraphy.

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