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Computationally evaluating and synthesizing Chinese calligraphy

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ABSTRACT

We present an approach for synthesizing Chinese calligraphy with a similar topological style from learning author's written works. Our first contribution is an algorithm to match the trajectory. Second contribution is a method to represent Chinese character topology via WF-histogram. Third contribution is an algorithm to take topological features as features and feed them into the evaluation model—that is Adaboost composed of support vector regressions (SVRs). Fourth contribution is a Genetic Algorithm (GA) introduced in the optimization glyph phase. Moreover, we introduce hypothesis testing and the decay function of transformation amplitude to improve the converge speed. The experiments demonstrate that our approach can obtain a similar topological style Chinese calligraphy with training samples.

1. Introduction

Chinese calligraphy history has experienced a long process and is a special traditional art. Recently, more researches are focused on Chinese character recognition but in everyday life our visual perception also induces a sense of how artistic Chinese calligraphy is. To the best of our knowledge, attempts to program a computer to appreciate and generate calligraphic art have been rare. To imbue computers with the ability to grade or create beauty is certainly a valuable problem in the AI field. Given a certain calligraphist works, the computer synthesizes more calligraphic characters with a similar style by learning his written works—that is generating a large scale calligraphic character set through the small one. Chinese character derived from pictographs, which evolved over time into symbols, many basic features recur in different Chinese characters. To make use of this redundancy, we extract strokes from author's works as elements, analyze the layout styles of strokes and recombine these elements according to the character topology style. Thus, the style of synthesized results includes the stroke shape and spatial arrangement factors. The technique can be potentially applied in many fields like designing font library, restoration of ancient works and more.

There have been many results of handwriting synthesis researches on English, Latin or Japanese characters [1–5]. These studies are mainly to synthesize users' trajectories by sample statistics. Compared with generating some other characters with new style, reproducing Chinese calligraphy characters is much more difficult because the number of Chinese character is much times larger than other characters' and Chinese character topology is also more complex than others'. The algorithms on synthesizing Chinese calligraphy can be mainly grouped into three categories. The first category is on the basis of analogous reasoning idea [6–9]. These methods greatly depend on non-rigid matching using character image – that is getting a new style character through weighting the positions of the corresponding points. However, non-rigid matching needs further research in the pattern recognition field. Their results are similar to the training samples and in extreme cases they are the same as the samples themselves. The second one is based on some rules. Lai et al. studied the problem of numerically evaluating the beauty of calligraphic characters through designing some experience rules and a heuristic approach [10]. As a result of the complexity of Chinese characters, their method is difficult to embody the comprehensive writing's style. The third one is to substitute stroke contour for user's trajectories directly. Zhang et al. designed a system to render the users handwriting characters with a specific style [11]. To a large extent, their method greatly relies on initial condition, i.e., the outputs are impacted seriously by the user's original trajectories. In addition, Shi et al. used Bayesian dynamic model to characterize the character generation process [12]. In [13], Shi et al. proposed a framework to effectively generate a new hybrid character type by means of integrating local contour feature of Chinese calligraphy with structural feature of font in the computer system.

The problem of synthesis Chinese calligraphy can be divided into three subproblems – that is how to represent character topology, evaluate style and optimize glyph. Xu et al. adapt the

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overlapping between the bounding boxes of two strokes to denote the stroke layout [6,8]. Due to the diversity of stroke, the same bounding box may include many different kinds of the stroke. Thus employing the bounding box is not good enough to represent character topology. Low et al. employed the skeletonization approach to represent Chinese character and use the resulting written strokes for optimized matching [14]. They used the shortest path method that is represented by the end node pair and junction node pair in the character for matching. In their method, the factor of stroke area is ignored. However this factor is also important to the spatial relationship between strokes. Lai et al. proposed structurally based character composition expression for composing these unrepresented Chinese characters unambiguously on the basis of the hierarchical relationships [10]. They divided the character composition into horizontal, vertical and surround type. These categories are limited to express Chinese character. To grade the beauty of character, the back propagation neural network (BPNN) is used to evaluate the visual qualities of Chinese calligraphy [15]. As is well known, BPNN is an algorithm of local optimization, but in our work we adopt global optimization algorithms as rating Chinese calligraphy style and synthesizing glyph.

Fig. 1 shows an overview of our work. Given user-specified trajectories, the prototype system first matches trajectories from the stroke library. Next, replace these trajectories with strokes. Finally, after learning from the topological relationship style in the off-line state by trained samples, the system optimizes the Chinese calligraphic characters under the object function.

Our main contribution is an evaluating and synthesizing Chinese calligraphy model. Our model includes an algorithm to match trajectories, WF-histogram to represent character topology, Adaboost composed of SVRs to grade the artistic style and GA to optimize glyph.

2. Stroke representing and matching

2.1. Stroke representing

Due to corrosion strokes scanned from ancient calligraphic works have blur edge. In addition to reduce the computing complexity and save the space, we employ B-spline curve to represent the stroke contour. Automatic calculation of the stroke skeleton is also difficult to get good results, so we replace it with the interactive trajectory. The controlling points of B-spline curve and the trajectory represent the stroke. Thus a stroke library with a special style can be constructed of which strokes are recombined to synthesize new characters (see Fig. 2).

2.2. Stroke matching

Trajectory is the path passed by the brush tip when an author writes characters. Chinese calligraphy emphasizes the writing method greatly. Trajectories can distinguish the difference of strokes. So we can recognize the stroke types by their trajectories. More concretely, for a certain trajectory Tr, we assume that it consists of I points $S_0, S_1, \ldots, S_{I-1}$. We take the first end point S_0 as the example to describe the property. The point O_1 satisfies $|\overrightarrow{S_0O_1}| = |\overrightarrow{S_{I-1}O_1}|$. Then, rotate the vector $\overrightarrow{S_0O_1}$ anti-clockwise 90° around O_1 and get the origin point O. After that we draw rays by every 1° and get a series of intersection points with Tr. Without loss of generality, let $P_0, P_1, \ldots, P_{m-1}$ be the intersection points at the k^0 ray. Then the distance at k^0 is $d_k = \sum_{i=0}^{m-1} |\overrightarrow{OP_i}|$. The maximum distance is $d_{max} = \max\{d_k | 0 \le k \le 359\}$, the minimum distance is $d_{min} = \min\{d_k | 0 \le k \le 359\}$ and the relative distance is denoted by $D_i = (d_i - d_{min})/(d_{max} - d_{min} + \varepsilon)$ where ε is a small positive number to avoid the division by-zero error. Thus, we get a360-dimensional vector F_0 (see Fig. 3). Likewise the property of other points in Tr is computed as described before. Matrix $F = [F_0, F_1, \ldots, F_{I-1}]_{360*I}$ is formed by feature vectors. Compute correlation matrix $A = (1/I) \sum_{i=0}^{I-1} F_i F_i^T$, and we have that $A = U \Lambda U^T$ where $\Lambda = diag\{\lambda_0, \lambda_1, \ldots, \lambda_{359}\}$ and U is a matrix constructed by eigenvector. Let $E = U^T F$ and $E = [e_0, e_1, \ldots, e_{I-1}]$. Here, e_i denotes the feature vector of the ith point. In practice, we only keep the former L components of e_i as the feature of the ith point ($L < 360$). To calculate the similarity of trajectory, we define the equations as follows.

Definition 1. Let a and b denote the point of the trajectory Tr_a and Tr_b respectively. The difference between a and b is

$$dif(a,b) = \frac{1}{2} \sum_{j=0}^{L-1} \frac{(e_{a,j} - e_{b,j})^2}{e_{a,j} + e_{b,j}} \tag{1}$$

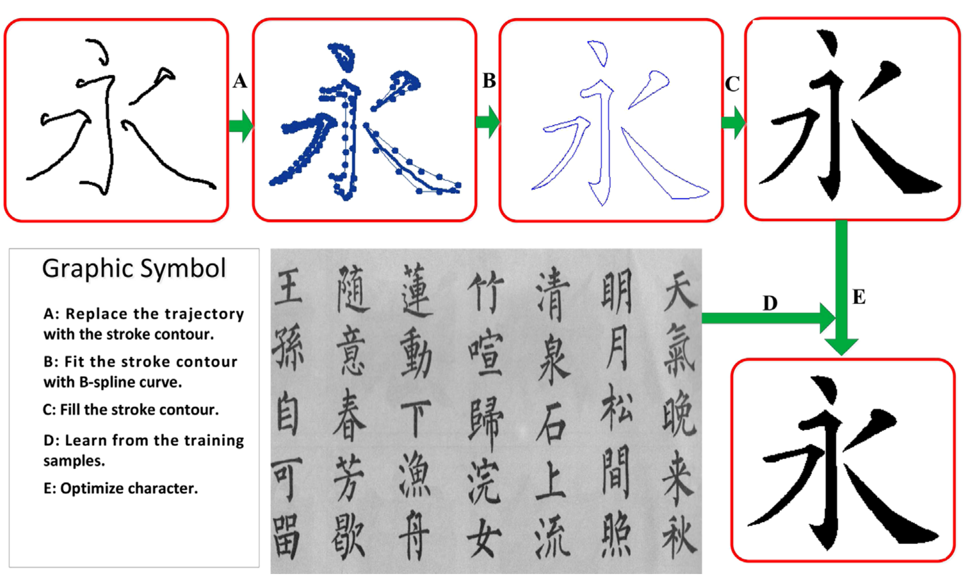

Fig. 1. The overview of evaluating and synthesizing Chinese calligraphy.