Automatic Creation of Artistic Chinese Calligraphy

Wei Li
Department of Computer Science and Technology, Xiamen University of Technology, Xiamen 361024, China
Email: liweipla@gmail.com

Changle Zhou
Cognitive Science Department, Xiamen University, Xiamen 361005, China
Fujian Key Laboratory of the Brain-like Intelligent Systems, Xiamen University, Xiamen 361005, China
Email: dozero@xmu.edu.cn

***Abstract*—We present an approach to creating Chinese calligraphy with particular style from learning author's written works automatically. Our first contribution is a method to represent Chinese character topology via fuzzy relative position. Our second contribution is an algorithm to take topological features as features fed into the evaluation model, which is a decision tree algorithm. Our third contribution is an algorithm of heuristic search in the optimization glyph phase. To improve the converge speed, we introduce hypothesis testing and the decay function of transformation amplitude. The experiments demonstrate our algorithm can obtain the similar style Chinese calligraphy with training samples.**

***Index Terms*—Calligraphy, Creation, Evaluation artistic style**

I. INTRODUCTION

Chinese calligraphy is a particular traditional art form. In recent years, the automatic creation calligraphy becomes a new research hotspot through the computer in AI. However, there exist few characters that represent a distinctive style of a given calligraphist. If we can synthesize the similar style glyph by learning from the written works (i.e. generation a large-scale character set via the small-scale), we will obtain more Chinese calligraphy characters. The technique can be potentially applied in many fields like expanding font library, repairing ancient works, designing multimedia, etc. Thus, it is meaningful to inherit and protect culture heritage.

Chinese characters derived from pictographs, which evolved over time into symbols, many basic features recur in different Chinese characters. To take advantage of this redundancy, we extract stokes from author's works reassemble these "components" according to the style.

Most work on computerized calligraphic handwriting synthesis has focused on English, Lartin or Japanese characters [1-5]. Automatic generating Chinese calligraphic writing is particularly challenging because the Chinese character set is many times larger than those and the writing styles are much more diversified owing to the complexity of character composition.

The synthesis of Chinese characters can be grouped into two categories: The first one is based on the analogous reasoning method [6-9] in which the corresponding point or topology between samples is matched and a character with new style is generated by weighted average in these corresponding components. This method depends heavily on many samples to the same character and non-rigid point matching is also a thorny issue for pattern recognition. The results are similar to the samples. The second category involves rule-based method using which we reconstruct a new style character by some rules. For the complexity of Chinese character, only several rules are incomplete to capture the style of Chinese character. In addition, some researchers also substitute strokes for the trajectories directly to synthesize Chinese calligraphy [10]. Their work greatly depends on the user's initial trajectories.

How to rationally represent the Chinese character topology is key to synthesize calligraphy. Xu et al. [7, 9] employ the overlapping between the bounding boxes of two strokes to denote the character topology. Because stroke shape can highly impact their spatial relationship, the bounding box range is too big to subtly capture the stroke layout. Low et al. [11] employ the distance between the stroke end point and cross point to express the Chinese character topology. They ignore that the stroke area is also an important factor to the stroke relationship. For instance, even the stroke area changed, their spatial relationship may be invariant. However, we can capture the difference via human vision. Lai et al. [12] simply divided the Chinese character into the horizontal, vertical and surrounding topology. In practice, even for the same topology, their style may be different. Furthermore, they didn't consider the stroke relationship in the radical.

In this paper, we present an example-based Chinese calligraphy synthesis method using which we can

Correspond Author: Wei Li (liweipla@gmail.com).
He has a Ph.D. and Changle Zhou is a professor at Xiamen University.
This work was supported by the National Natural Science Foundation of China under grant no. 61273338 and CCF Opening Project of Beauty Evaluation of Chinese character under grant no. CCF-2012-01-06.

doi:10.4304/jsw.8.12.3048-3054

overcome the above disadvantage. First we capture the subtle topological changes using fuzzy relative position to represent the character topology. Second, we evaluate the topological style using decision tree. Third, we improve the converge speed of object function through the testing hypothesis and the decay function introduced in the optimization process.

Fig. 1 demonstrates the overview of example-based Chinese calligraphy synthesis. Given trajectories as input, the system first retrievals strokes from stroke library by recognition trajectories. By using fuzzy relative position [13] to represent the spatial relations of strokes, we extract feature vector in the glyph. This feature vector is then fed into the optimization engine, which yields a modified feature vector with a higher predicted score than that of the original vector. Next, we readjust the strokes in the glyph to generate the new character topology as close as possible to the modified feature. Thus, we can get a Chinese calligraphy character with special style.

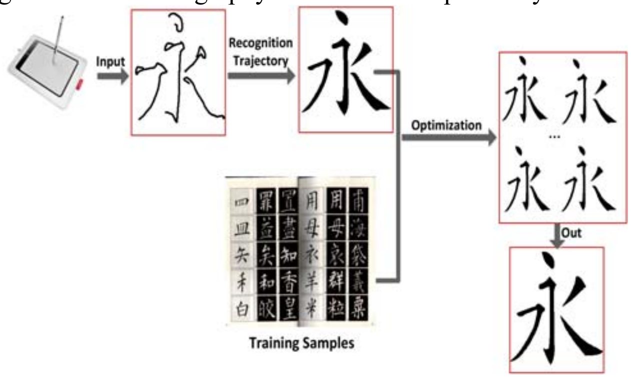

Figure 1. Example-based Chinese calligraphy synthesis.

II. Stroke Retrieval by Trajectory Recognition

Stroke glyphs scanned from ancient China's calligraphic works have incomplete edge due to corrosion. Spline curves can be used to overcome the drawback, so we can obtain the controlling points along stroke contours interactively to fit the edges with B-spline curves. In addition, automatic extraction stroke skeleton remains difficult. Thus, we substitute the calligrapher's trajectory for the skeleton of stroke. By defining a one-to-one mapping in the contour and trajectory, we can construct a stroke library. The stroke consists of the contour controlling points and trajectory (see Fig. 2). Given a user's trajectory, the system can retrieval the corresponding contour. In the recognition trajectory phase, we employ the HOG matching algorithm proposed by [14].

III. Representing Character Topology

Chinese character topology is viewed as the relationship of strokes composed of Chinese character or the layout of these strokes. Bloch et al. [13] proposed a morphological and fuzzy pattern-matching approach in

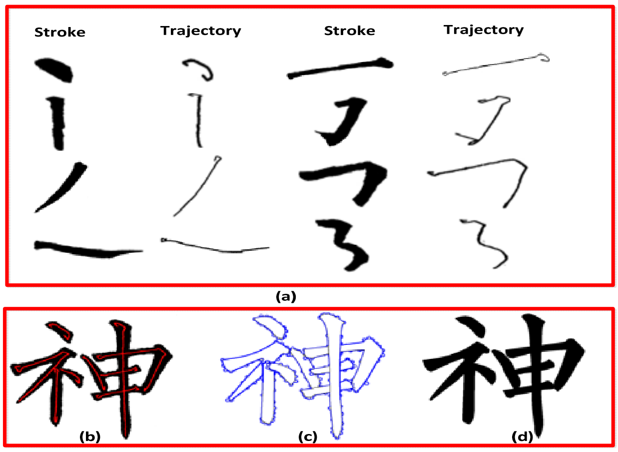

Figure 2. Representation the stroke by the trajectory and contour. (a) is a part of stroke and corresponding to trajectory. (b) is original Chinese character "god", accommodating the trajectories and contours. (c) is fitted by B-spline curves. (d) is filled by scan-line filling algorithm and removed the controlling points of contours.

representing the relative position between two objects in a fuzzy set framework. Inspired by them, we introduce the arc length weighted function and the distance weighted function based on the concept "possibility degree" to represent the relationship between two strokes. By the relationship between strokes, we can represent the Chinese character topology. First, we define a function $\varphi: [0,\pi] \rightarrow [0,1]$. (Eq. 1)

$$\varphi(\alpha) = \begin{cases} \cos^2\left(\frac{\alpha}{2}\right), \alpha \in [0,\pi] \\ 0, \text{otherwise} \end{cases} \quad (1)$$

Given direction $\vec{\delta}$, reference stroke S_r and point p, we compute the membership value for " p is in direction $\vec{\delta}$ of S_r" by $O(p, S_r, \vec{\delta})$ (Eq. 2). For instance, if $O(p, S_r, 0) = 1$, p is to the east of S_r. If $O(p, S_r, 0) = 0$, p is not to the east of S_r. If $O(p, S_r, 0) = 0.5$, the membership value that p is to the east of S_r is 0.5.

$$O(p, S_r, \vec{\delta}) = \max_{q \in S_r}\left\{\varphi\left(\arccos\left(\frac{\overrightarrow{qp}\cdot\vec{\delta}}{|\overrightarrow{qp}|\cdot|\vec{\delta}|}\right)\right)\right\} \quad (2)$$

$$q_p = \operatorname{argmax}_{q \in S_r}\left\{\varphi\left(\arccos\left(\frac{\overrightarrow{qp}\cdot\vec{\delta}}{|\overrightarrow{qp}|\cdot|\vec{\delta}|}\right)\right)\right\} \quad (3)$$

We construct a neighborhood $N(q_p, \varepsilon)$ and take q_p as center and ε as radius, where ε is a small positive number. $l(q_p, \varepsilon)$ is the arc length of $N(q_p, \varepsilon)$ (simplified for l_p). The larger l_p is, the denser the point of $N(q_p, \varepsilon)$ is. Thus, q_p has much more contribution to the membership value for "p is in $\vec{\delta}$ direction". In addition, when the point $p \in S$ and $\acute{p} \in S$ have the same contribution to the membership value for "stroke S is in $\vec{\delta}$ direction of stroke S_r" by Eq. 2 and $p, \acute{p}$ satisfy $|\overrightarrow{pq_p}| < |\overrightarrow{\acute{p}q'_{\acute{p}}}|$, where the point q_p and $q'_{\acute{p}}$ are the corresponding point of p and $\acute{p}$ calculated by Eq. 2, respectively, we think that the point p has more contribution than $\acute{p}$ in the membership value for "stroke S is in $\vec{\delta}$ direction of stroke S_r". This is accordance with the phenomenon that most people pay more attention to the near object than the far. To distinguish the above case, we introduce distance weighted function defined as the Eq. 5.

$$\omega_{l_r}(p) = \frac{1}{\sqrt{2\pi}\sigma_{l_r}} \exp\left(-\frac{(l_p - \bar{l}_r)^2}{{\sigma_{l_r}}^2}\right), \tag{4}$$

where $l_p \approx \sum_{q_i,q_{i-1} \in N(q_p,\varepsilon)} |\overrightarrow{q_{i-1}q_i}|$.

$$\omega_d(p) = \frac{1}{\sqrt{2\pi}\sigma_d} \exp\left(-\frac{(l_p - \bar{d})^2}{{\sigma_d}^2}\right), \tag{5}$$

where $d_p = |\overrightarrow{q_p p}|$.

Specially, when there are n points $q_p^1, q_p^2, \cdots, q_p^n$ which satisfy Eq.3. corresponding to point p, we have that $d_p = \frac{1}{|S_r(\vec{\delta},p)|}\int_{q_p \in S_r(\vec{\delta},p)} \sqrt{|p - q_p|^2}\, d(q_p)$, where $|S_r(\vec{\delta},p)|$ denotes the number of solutions by Eq. 3.

We have considered the point distribution in stroke S_r. Stroke S is irregular in many cases. Point distribution in stroke S can affect highly the relationship between S and S_r. So we introduce the arc length weighted function with respect to the points in stroke S (Eq. 6).

$$\omega_l(p) = \frac{1}{\sqrt{2\pi}\sigma_l} \exp\left(-\frac{(l_p - \bar{l}_p)^2}{{\sigma_l}^2}\right), \tag{6}$$

where $l_p \approx \sum_{q_i,q_{i-1} \in N(p,\varepsilon)} |\overrightarrow{q_{i-1}q_i}|$.

The relationship between stroke S and S_r can be defined as Eq. 7.

$$R(S_r, S, \vec{\delta}) = \frac{1}{|S|}\int_{p \in S} \omega_{l_r}(p)\, \omega_d(p) \omega_l(p) O(p, S_r, \vec{\delta}) dp, \tag{7}$$

where $|S| = \int_{p \in S} \omega_{l_r}(p)\, \omega_d(p) \omega_l(p) dp$.

Let C be a Chinese character composed of stroke $S_1, S_2, \ldots, S_N$. Its topology can be defined as:

$$T_i(C) = \begin{bmatrix} R(S_1, S_1, \frac{2\pi i}{\Delta}) & \cdots & R(S_1, S_N, \frac{2\pi i}{\Delta}) \\ \vdots & \ddots & \vdots \\ R(S_N, S_1, \frac{2\pi i}{\Delta}) & \cdots & R(S_N, S_N, \frac{2\pi i}{\Delta}) \end{bmatrix} \tag{8}$$

Here, we divide the space into Δ subspaces according to angle (Δ mod 4=0). $\{\frac{2\pi i}{\Delta}\}_{i \in \{0,1,\ldots,\Delta-1\}}$ denotes referent direction set and is distributed in Cartesian plane evenly. In practice, we replace the local arc length with the ratio between the local neighborhood points and the contour points. The distances are normalized by the square root of the character's bounding box area to make them invariant of scale.

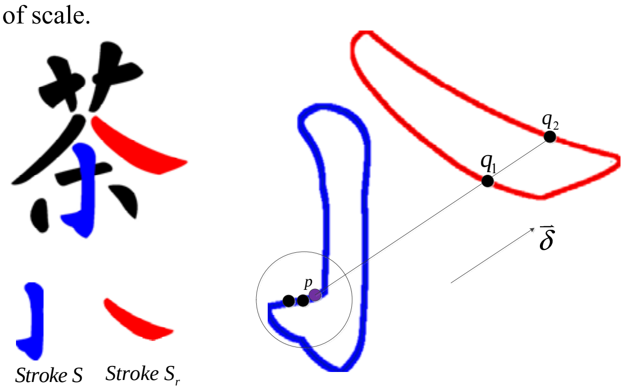

Figure 3. The spatial relationship between two strokes.

IV. Learning Style

The aesthetic style of Chinese calligraphy, to a large extent, is determined by the character topology. The number of Chinese character is huge, in order to greatly reduce the number of samples, inspired by Xu at el. [15] , we use the different features between the synthesis Chinese calligraphy and the corresponding Kai font character as feature vector. In our work, decision tree as evaluation model can avoid becoming stuck at local minima compared with the back propagation neural network employed by [15].

A. Extraction Feature

Given Chinese character C with style C_α and corresponding standard character C_β, to evaluate the spatial layout of C_α, we can make feature analysis by the fuzzy position representing character topology (Sec. III). For this purpose, a series of dissimilarity matrix can be constructed,

$$X_k = T_i(C_\alpha) - T_i(C_\beta), k = 0,1, \ldots, m-1 \tag{9}$$

After that, we define $Y_k = A_k^{-1/2} X_k A_k^{1/2}$ as the Laplacian matrices. Here, A_k is a diagonal matrix and its element value in (i,i) is the sum of the element values of the i^{th} row in X_k. Then the maximum element value, minimum element value, maximum absolute value, mean element value, median element value, and the first two eigenvalues can be calculated in matrix Y_k. Thus we obtain a total of 7*m features for character C_α and in our experiments, we set m=16.

B. Decision Tree based Aesthetics Evaluation

The calligraphic character aesthetics based on a decision tree learning algorithm is evaluated. We collect the samples from a copybook of calligraphy and the reassembling glyph via employing strokes or radicals with the special style. After that, we invite some calligraphers and students to give score for every sample. In our experiments, let Δ be 16 (Sec. III) and the 112-dimensional feature vectors and their corresponding grading scores (on a scale of 1 to 7) are used as training samples to construct a decision tree model. We employ an entropy minimization criterion to select attribute [16] and reduced-error pruning [17] to make tree pruning. Numerical attribute discretization is done based on methods described in [18]. Yin Lisheng et al. present a adaptive chaotic prediction algorithm of RBF neural network filtering model based on phase space reconstruction [19]. We may look upon decision tree induction as a method for attribute selection. During the learning phase, we only choose the most relevant attributes from the whole set of attributes for the construction of decision rules in the nodes.

V. Optimization

In order to get the particular writing style character, strokes are adjusted by affine transformation. With the number of stroke rising, complexity of the algorithm takes on the exponential growth. Based on the air distribution request of the mine ventilation network, carries on the optimized computation to the mine ventilation system network, fuses the dynamic perturbation and the simulated annealing to improve the harmony search algorithm, the improved harmony search algorithm enhances the convergent speed, has overcome certain limitations of the traditional ventilation network optimizing control algorithm [20]. Wei Wei et al. [21]

present a novel usage of the helpful action pruning technique in the Conformant-FF planner.

Inspired by them, in order to reduce the complexity, an approximate solution by heuristic search procedure is adopted in our work. The goal of the optimization process is to minimize a cost function, including the depth of the search space and the evaluation score, defined as $H(\emptyset) = \exp(\lambda_1 * D(\emptyset) - \lambda_2 * E(\emptyset))$. Here, $\emptyset$ is the state of node (i.e. stroke spatial layout feature), $D(\emptyset)$ denotes the depth from the root node to $\emptyset$, $E(\emptyset)$ is the evaluation score by decision tree (Sec. IV), λ_1 and λ_2 determine the relative weighting between the cost terms (in practice we set $\lambda_1 = 0.3, \lambda_2 = 0.7$). The basic move of the optimization modifies the position of a stroke and its size. That is $(T_i, S_i) \to (T_i + \delta T, S_i)$ or $(T_i, S_i) \to (T_i, S_i + \delta S)$, where $\delta T \sim N(\mu_T, \sigma_T^2)$ and $\delta S \sim N(\mu_S, \sigma_S^2)$, with $N(\mu, \sigma^2) = (2\pi\sigma^2)^{-\frac{1}{2}} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)$ a Gaussian distribution of mean μ and variance σ^2. Here, T_i and S_i denote the centre and diagonal distance of bounding box of the i^{th} stroke respectively. The translation direction includes left, right, top and bottom. According to hypothesis testing, we can infer whether the move is rational (That is, given significance α, we compute $P\left\{\left|\frac{\overline{\delta T}-\mu_T}{\sigma_T/\sqrt{M}}\right| > z_{\alpha/2}\right\} = \alpha$ and $P\left\{\left|\frac{\overline{\delta S}-\mu_S}{\sigma_S/\sqrt{M}}\right| > z_{\alpha/2}\right\} = \alpha$ to predict whether the move is correct, where $z_{\alpha/2}$ denotes quantile and M is the number of samples). With the increase of the grading score, the move range should be small step by step. To this end, we define a translation and scaling decay function as $\delta_{j+1}(T) = \exp(-\gamma_T - E(\emptyset_j))$ and $\delta_{j+1}(S) = \exp\left(-\gamma_S - E(\emptyset_j)\right)$, in practice $\gamma_T = 0.55$ and $\gamma_S = 0.90$. The algorithm selects the smallest $H(\emptyset)$ to move in each iteration. Repeating the above process, the algorithm will not terminate until $E(\emptyset) \geq 4$ or the depth of the search space is more than a threshold value. When the latter case appears, the algorithm will select the smallest $H(\emptyset)$ in the process as output.

VI. RESULTS

In this section, we demonstrate and discuss results obtained by our synthesis Chinese calligraphy algorithm. Fig. 4(a) outperforms Fig. 4(c), but generally, both are desirable. Compared with closely related approaches [10], our algorithm don't heavily rely on the initial topology so desirable glyphs are obtainable even with mediocre scribing.

In order to demonstrate the efficacy of our optimization approach, we take the Chinese character "tai" as an example. As shown in Fig. 5, when the iteration is more than 40 times, the move amplitude is decreasing obviously and the visual effect becomes better and better.

Fig. 6 shows the graph of the translation and scaling amplitude decay function (see Section V). By statistic, we found that the translation and scaling satisfy $T \sim N(0.15，0.04)$ and $S \sim N(0.2，0.03)$. As shown in Fig. 6(c) and 6(d), when the grading score is lower, the large amplitude needs to be adjusted, however, with the increasing of the evaluation degree, the smaller amplitude to be moved. Thus, on the one hand, the convergence speed can be improved at the beginning. On the other hand, the algorithm can consolidate the "achievements" against returning "poor" state. In our experiments, we set $\gamma_T = 0.55$ and $\gamma_S = 0.90$. With the grading score increasing, the transformation amplitude approximates 0.

To test our evaluation algorithm, we invited seven calligraphists to rate the visual quality of each sample character. Table I shows a comparison of the human grading results with those from our algorithm. Average error is less than 7%, the result approximate the human grading.

Fig. 7~9 show a verse of poetry written in automatically generated calligraphy characters.

VII. CONCLUSION

In this paper, we proposed a novel method to represent the character topology, which can capture subtle changes of strokes. In addition, we adopt decision tree evaluation model to grade the calligraphy style. To improve the convergence speed, we introduce the testing hypothesis and the move amplitude decay function to transform glyph according to the evaluation score automatically in the optimization process. We explore generating the large-scale character set via the small-scale with the similar style. Apart from the character topology, 'hollow-stoke' is also one of important style, which can be affected by the writer's mood. The same writer with different mood and feeling may also write glyph with different style. So mood can highly affect human's creation. In the future, we will consider these factors in the calligraphy synthesis.

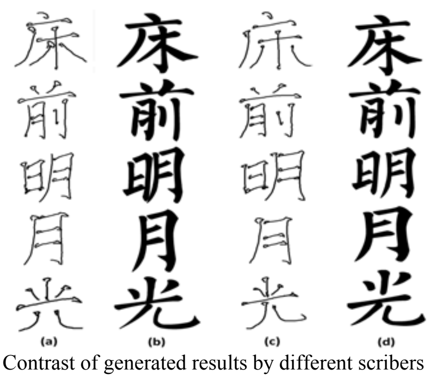

Figure 4. Contrast of generated results by different scribers and scripts. (a) and (c) are the different users' trajectories respectively. (b) and (d) are the optimization results using our algorithm.

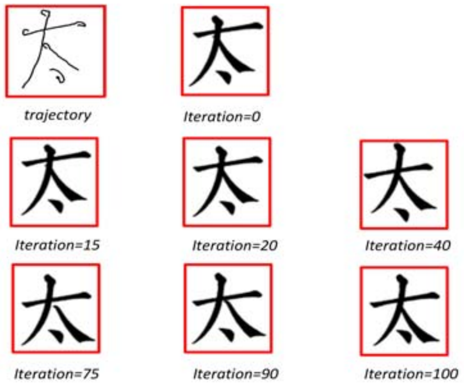

Figure 5. The optimization process of the character “tai”

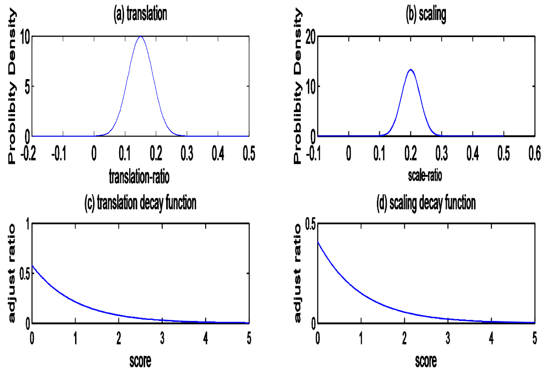

Figure 6. The distribution and decay function of transformation amplitude.

TABLE I.
COMPARISON OF ALGORITHMIC AND HUMAN SPATIAL-LAYOUT GRADING

Character	Algorithm Grading	Human Grading	Character	Algorithm Grading	Human Grading
福	6	7	福	3	3
福	6	6	福	4	3
福	3	3	福	2	3
福	2	2	福	6	5

Figure 7. Generation a idiom with LIU Gongquan’s style using our prototype system (LIU Gongquan is very famous calligraphist in the Tang Dynasty).


Figure 8. Generation a poem “brave the wind and the waves”.

Figure 9. Generation LI-Bai's poem (LI-Bai is a famous poet in the Tang Dynasty).

REFERENCES

[1] Rapee Suveeranont and Takeo Igarashi, "Example-based automatic font generation," Smart Graphics Lecture Notes in Computer Science, Springer, vol. 6133, pp. 127-138, 2010.

[2] Ján Dolinský and Hideyuki Takagi, "Analysis and modeling of naturalness in handwritten characters," IEEE Transactions on Neural Networks, Institute of Electrical and Electronics Engineers Inc, vol.20, pp. 1540-1553, 2009.

[3] Zhouchen Lin and Liang Wan, "Style-preserving English handwriting synthesis," Pattern Recognition, Elsevier Ltd, vol. 40, pp. 2097-2109, 2007.

[4] Hyunil Choi, Sung-Jung Cho, Jim H Kim, "Generation of handwritten characters with bayesian network based on line handwriting recognizers," in Seventh International Conference on Document Analysis and Recognition, pp. 995-999, 2003.

[5] Jue Wang, Chen Yu, Ying Qing Xu, Heung Yeung Shum, Liang Ji, "Learning-based cursive handwriting synthesis," in Frontiers in Handwriting Recognition, 2002. Proceedings. Eighth International Workshop on, pp. 157-162, 2002.

[6] Xiafen Zhang, Guangzhong Liu, "Chinese Calligraphy Character Image Synthesis Based on Retrieval," Lecture Notes in Computer Science, Springer Verlag, vol. 5879 LNCS, pp. 167-178, 2009.

[7] Songhua Xu, Hao Jiang, Tao Jin, Francis C.M. Lau, Yunhe Pan, "Automatic Generation of Chinese Calligraphic Writings with Style Imitation," IEEE Intelligent Systems, Institute of Electrical and El-ectronics Engineers Inc. vol. 24, no. 2, pp. 44-53, 2009.

[8] Jun Dong, Miao Xu, Xian-Jun Zhang, Yan-Qing Gao, Yun-he Pan, "The creation process of Chinese calligraphy and emulation of imagery thinking," IEEE Intelligent Systems, Institute of Electrical and Electronics Engineers Inc., vol. 23, no. 6, pp. 56-62, 2008.

[9] Songhua Xu, Francis C.M. Lau, William K. Cheung, Yunhe Pan, "Automatic generation of artistic Chinese Calligraphy," IEEE Intelligent Systems, Institute of Electrical and Electronics Engineers Inc., vol. 20, no. 3, pp. 32-39, 2005.

[10] Zhenting Zhang, Jiangqin Wu, Kai Yu, "Chinese calligraphy specific style rendering system, " 10th Annual Joint Conference on Digital Libraries, JCDL 2010, Association for Computing Machiney, pp. 99-108, 2010.

[11] Jing-Hong Low, Chee-Onn Wong, Kirak Kim, Keechul Jung, Eunjung Han, Hwangkyu Yang, "Using Skeletonization and Shortest Skeleton Path Approach for Chinese Character Representation, " Digital Image Computing: Techniques and Applications, DICTA 2008, pp. 472-479, 2008.

[12] Pak-Keung Lai, Dit-Yan Yeung, Man-Chi Pong, "A Heuristic Search Approach to Chinese Glyph Generation Using Hierarchical Character Composition," Computer Processing of Oriental Languages, pp. 281-297, 1997.

[13] Bloch Isabelle, "Fuzzy relative position between objects in image processing: A morphological approach," IEEE Transactions on Pattern Analysis and Machine Intelligence, IEEE, vol. 21, pp. 634-643, 1999.

[14] Navneet Dalal and Bill Triggs, "Histograms of Oriented Gradients for Human Detection, " Proceedings-2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition, pp. 886-893, 2005.

[15] Songhua Xu, Hao Jiang, Francis C.M. Lau, Yunhe Pan, "Computationally Evaluating and Reproducing the Beauty of Chinese Calligraphy, " IEEE Intelligent Systems, Institute of Electrical and Electronics Engineers Inc., vol.27, no. 3, pp. 63-72, 2012.

[16] J.R.Quinlan, "Induction of decision trees," Machine Learning, vol 1, pp. 81~106, 1986.

[17] J.R.Quinlan, "Simplifying decision trees, "International Journal of man-machine studies, vol. 27, pp.221~234, 1987.

[18] Perner, P.Trautzsch, S., 1998. On feature partitioning for decision tree Induction. In: Amin, A., Dori, D., Pudil, P., Freeman, H., (Eds), SSPR98 and SPR98. Springer, Berlin, pp.475~482.

[19] Lisheng Yin, Yigang He, Xueping Dong and Zhaoquan Lu, "Adaptive Chaotic Prediction Algorithm of RBF Neural Network Filtering Model Based on Phase Space Reconstruction, " Journal of Computers, Vol. 8, No. 6, pp.1449-1455, 2013.

[20] Jinxue Sui, Li Yang, Zhilin Zhu, Hui Fang and Hua Zhen, "Mine Ventilation Optimization Analysis and Airflow Control Based on Harmony Annealing Search, " Journal of Computers, vol. 6, no. 6, pp. 1270-1277, 2011.

[21] Wei Wei, Dantong Ouyang, Tingting Zou and Shuai Lu, "A Novel Heuristic Usage of Helpful Actions for Conformant-FF System, " Journal of Computers, Vol. 8, No. 6, pp. 1385-1393, 2013.

Wei Li has a Ph.D. at Xiamen University. His research interests includes AI, computer graphics, human-computer interaction. Li received Master degree from Inner Mongolia University in 2010. Contact him at liweipla@gmail.com.

Changle Zhou is a professor at Xiamen University at present. His research interests includes art cognitive, AI, pattern recognition, computer-aided design and computer art. Zhou receive Ph.D. from Peking University in 1990.