8

Principles of Automatic Generation of Artistic Chinese Calligraphy

8.1 Overview

In this chapter we will introduce a novel intelligent system which can automatically generate new Chinese calligraphic artwork to meet visually aesthetic requirements. The system first extracts the hierarchical parametric representations of Chinese characters from input images of existing calligraphic style to form a compact set of training examples. Using a six-layer hierarchical representation, the extraction results are stored in a small structural stroke database, which are then exploited to form a continuous calligraphy knowledge space. The space is spanned by character examples of different styles (knowledge sources) which are aggregated and aligned according to a proposed constraint-based analogous reasoning process. By also incorporating a set of simple and yet effective geometric constraints, the proposed system can generate novel calligraphic styles that are aesthetically appealing. Samples of novel calligraphic artwork produced using the system are presented to demonstrate the effectiveness of our approach. The combination of knowledge from various input sources creates a huge space for the intelligent system to explore and produce new styles of calligraphy. Possible applications of the proposed system are also discussed.

Without ambiguity we will abbreviate the term “automatic generation of artistic Chinese calligraphy” to “automatic calligraphy generation” from now on.

8.2 Introduction

Chinese calligraphy is among the finest and most important of all Chinese art forms, and an inseparable part of Chinese history. It can convey not just what was explicitly put in a written message but also the emotion of the writer. The very delicate aesthetic effects achievable by Chinese calligraphy are generally considered to be unique among all calligraphic arts because the normal shape and topological structure of the font in aesthetic Chinese calligraphy can be largely distorted for its better perceptual impression. Chinese calligraphy is also an integral part of traditional Chinese painting, e.g. Fig. 8.1(a). The calligraphy is there not just as an annotation, but also because it can affect the overall visual and perhaps also emotional perception of the viewer to the painting. As such, artistic Chinese calligraphy is often more preferred than printed types in Asian societies for banners and signs, and headers of newspapers, etc. (Fig. 8.1(b)). A latest example is the official logo of the 2008 Beijing Olympics Games (http://en.beijing-2008.org/).

(a) (b)

Fig. 8.1. Wide use of artistic Chinese calligraphy in Asian societies: (a) Chinese painting with calligraphy; (b) top: the roof of a Kong Zi (Confucius) temple; bottom: the header of the China Daily newspaper

Other than artists, it has also caught the attention of scientists who are interested in computer-assisted art. Chinese calligraphy is predominantly done using a brush. Computerizing Chinese calligraphy is challenging as the shapes of brush strokes as well as the topology over multiple strokes can be very complex. In comparison, Western calligraphy which is based on Latin alphabets is much simpler and easier to computerize.

The most common use of calligraphic art in the digital world is to create typographic or artistic fonts for display or printing, for which Knuth has done some pioneering work [Knu79]. Chinese calligraphy is predominantly carried out using a soft hair brush. Generating artistically appealing Chinese calligraphic artwork using the brush can be highly challenging. The large character set (consisting of 3,000+ commonly used characters) of the Chinese language itself presents a problem. Being able to master some of the characters does not mean that one can also write the other characters as satisfactorily. Similarly, one who is good in one or more styles is not necessarily also good in other styles, let alone able to create new styles in calligraphy. This is where the computer may step in and provide some help.

Calligraphic art is based on a font, which is a set of printer's type of the same size and face. Cubic Bézier curves and straight lines can be used to describe font shapes [Chu90, NTN93]. For artistic rendering, researchers have tried to model the brush used in calligraphy, such as [Str86] where the brush is modeled as a collection of bristles which evolve over the course of the stroke. In [XTLP02] a virtual brush based on solid modeling was demonstrated as a feasible interactive tool for creating realistic Chinese calligraphic writings. In [Blu67] the authors gave a detailed analysis of the writing effects that hairy brushes could produce. There have also been attempts at automatic generation of new fonts, such as [PMZS97] where the authors employed an algebra of geometric shapes to generate fonts by mixing existing fonts. But calligraphy can go beyond the boundaries of fonts; for example, it is possible to mix different styles and sizes of characters in a calligraphic artwork.

There has not been any published work on automatic creation (not just imitation) of beautiful calligraphic artwork using existing calligraphy as learning samples. This chapter proposes and describes such an intelligent system. We discuss the underlying principles and theories, and present the calligraphic results generated by a prototype we implemented. Our prototype system is able to generate brand new Chinese calligraphic artwork fully automatically. The number of input training samples used is very small.

In this chapter we propose an intelligent system which can automatically generate novel and yet artistically appealing Chinese calligraphic artwork based on a small number of training examples of existing calligraphic styles. The essential idea is to learn (good existing styles) and synthesize (beautiful new styles). The system first recovers the shapes of the training examples and represents them using a hierarchical parameterization. Then an analogous reasoning process is adopted to: 1) align the shape representations of the training examples to create a flexible model; 2) to generate novel calligraphic artwork; and 3) to remove aesthetically unacceptable candidates based on some simple but effective aesthetic constraints.

To demonstrate the feasibility of the proposed methodology, we have implemented a prototype system which can generate brand new Chinese calligraphic artwork fully automatically when given as input a small training set (typically below 10 for each character). To the best of our knowledge, there has not yet been any published work on the same approach. One remotely related project is the simulation of creativity in jazz performance [RG94], where artistic activities are also modeled using analogous reasoning.

The structure of the chapter is as follows. Sect. 8.3 formulates the problem and provides an overview of the system. Sect. 8.4 presents the hierarchical parametric representation of Chinese characters. Sect. 8.5 discusses how the training examples are analyzed and parameterized. Sect. 8.6 explains the proposed analogous reasoning process for automatic generation of new Chinese calligraphic characters. Sect. 8.7 discusses how aesthetic geometrical constraints can be incorporated into the system to reject unacceptable candidates from the output. Sect. 8.8 gives the experimental results. Sect. 8.9 discusses possible applications of our system in addition to generating Chinese calligraphy. Sect. 8.10 concludes the chapter and suggests some possible directions for future research.

8.3 Problem Formulation and Overall System Architecture

Let $\mathcal{P}$ denote a model with a parameterization $\mathbf{E}$ that is flexible enough to represent a class of highly deformable shapes (a Chinese character of different styles in our case). Normally, constructing a flexible model requires significant effort. On the other hand, an arbitrary instantiation from a flexible model could easily result in unacceptable results. Thus, generating novel and yet aesthetically appealing calligraphy using the model-based approach is by no means straightforward. Our approach is to make use of a constraint-based analogous reasoning process, which we apply to a set of given training examples. The basic idea of analogous reasoning is to fuse knowledge from multiple sources to support a restricted form of reasoning [Sim75]. In our case the *knowledge sources* are the *training examples* (which are in the form of images), and these two terms will be used interchangeably throughout this chapter.

Our proposed analogous reasoning process consists of three major phases: *shape decomposition*, *calligraphic model generation from examples*, and *artistic calligraphy generation*.

Calligraphic shape decomposition. *Shape decomposition* (or recovery) of a given training example is equivalent to the problem of extracting structural features for constructing a reference model $\mathbf{P}$. The reference model is an instance of the model $\mathcal{P}$ to best represent the input example. The underlying mechanism is character stroke segmentation/extraction.

Calligraphic model generation from examples. Given n reference models $\{\mathbf{P}_i\}$ constructed from a set of training examples, a family of novel shapes $\mathbf{P}(\omega)$ can be defined by *blending* the n reference models, $\{\mathbf{P}_i\}$, where the blending steps include: 1) identifying the correspondence of structure features among the reference models, and 2) combining the aligned models, by interpolation/extrapolation of the parameterization $\{\mathbf{E}\}$. Note that the newly derived shape family can be perceived as "re-parameterization" via the blending parameter, ω, which controls the contribution of each training example.

Artistic calligraphy generation. Given $\mathbf{P}(\omega)$ and a set of aesthetics-related geometrical constraints, artistic calligraphic artwork can be obtained by identifying some ω which satisfies the given constraints.

Fig. 8.2 shows the overall architecture of the proposed intelligent calligraphy generation system. At the heart of the system is an analogous reasoning

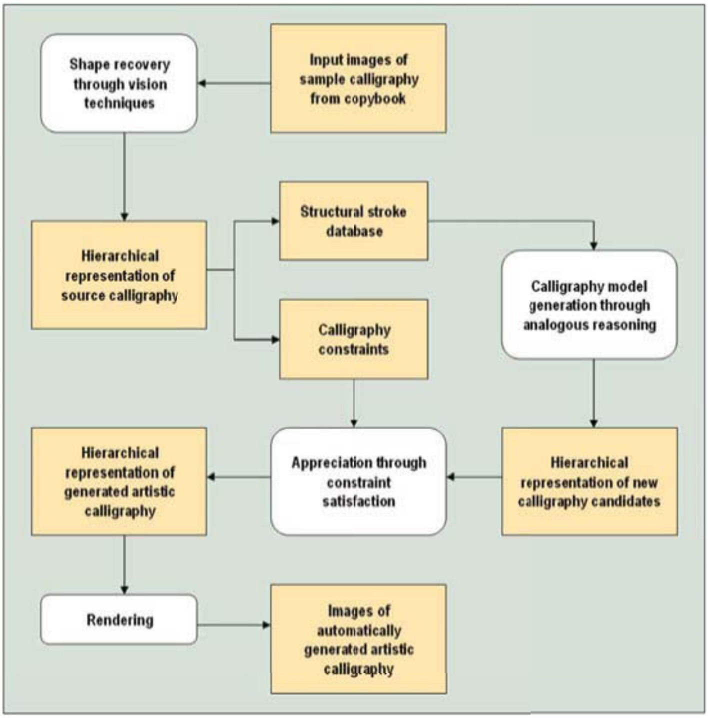


Fig. 8.2. Architecture of our intelligent calligraphy generation system

component that creates new calligraphy based on training examples and satisfying all the aesthetic constraints. In our experiments the training examples come from printed "copybooks" that present multiple calligraphic styles.

Our simulated analogous reasoning process is essentially data prediction (either interpolation or extrapolation) subject to the aesthetical constraints. For convenience we abbreviate "analogous reasoning process" to ARP and the current "simulated analogous reasoning process" to SARP.

The system has three main components. The first component learns and produces facsimiles of the existent calligraphic artwork in a hierarchical and parametric form; these facsimiles form a calligraphic knowledge base serving as the knowledge source for the SARP. The second component generates new calligraphic artwork automatically through the SARP. The third component applies constraint satisfaction to admit only those generated results that are aesthetically acceptable. The three components are referred to as the *facsimile component*, the *creation component*, and the *appreciation component*, respectively. The examination results led us to conclude that our approach is practical and the system is capable of generating acceptable outputs.

8.4 Hierarchical and Parametric Representation

No reasoning is possible and efficient without suitable knowledge representation. Before we elaborate on our intelligent calligraphy generation system based on analogous reasoning, we will first introduce our hierarchical and parametric representation of calligraphic artwork, which contributes tangibly to the overall system performance and reasoning capability.

In our system we treat Chinese characters and calligraphic artwork as images that are in a parametric form. This facilitates automatic processing of knowledge. Modern Chinese characters are derived from pictographs of complex shapes (see Fig. 8.5 for an example). The earliest Chinese characters are pictographs, which project meanings through shapes and images in an intuitive fashion. Over time these characters gradually became symbols and many basic features in different Chinese characters occur recurrently. To take advantage of this representation redundancy, we devise a hierarchical representation for Chinese characters.

8.4.1 Hierarchical Representation

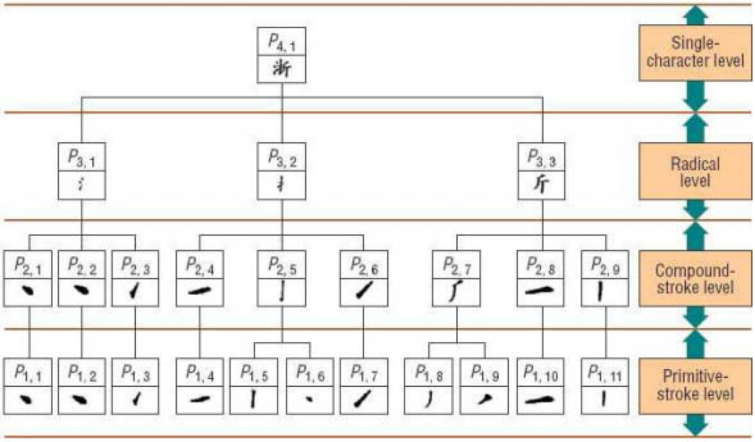
It can be easily observed that many local features recur in many different Chinese characters frequently. To capitalize on this image information redundancy, we introduce a hierarchical representation of Chinese calligraphy. A piece of Chinese calligraphy as an image is decomposed into six layers (or levels): the constructive ellipse layer, the primitive stroke layer, the compound stroke layer, the radical layer, the single-character layer, and the complete artwork layer (see Fig. 8.3(b)). This hierarchical representation can avoid much redundancy when storing the characters, and its various granularity makes SARP more effective and the input reasoning source as well as the output reasoning results more reusable. These six layers represent the calligraphic artwork parametrically. All the input parametric representations of the calligraphic artwork together form a reasoning space for the SARP to generate new aesthetic calligraphic artwork automatically.

The parametric representations adopted at all levels (to be described in the next subsection) together form the parameter space **E** for modeling Chinese calligraphic artwork.

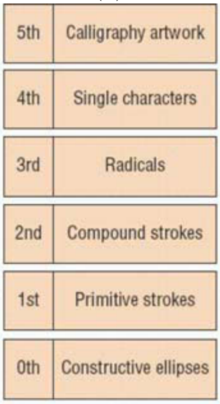
For the prototype we have implemented 5 typical and most frequently occurring primitive strokes (point strokes, horizontal strokes, vertical strokes, left slanting strokes and right slanting strokes), 24 typical and most frequently occurring compound strokes, and 36 radicals are used, as shown in Fig. 8.4. Fig. 8.3(a) shows the hierarchical representation of the Chinese character "zhe", as in "Zhejiang", the beautiful coastal province well known for its wealth of scenic spots.

8.4.2 Six Levels of Parametric Representation

At Level 0 of the hierarchical representation, an artwork is viewed as a collection of ellipses. These ellipses are called the "constructive ellipses" of the

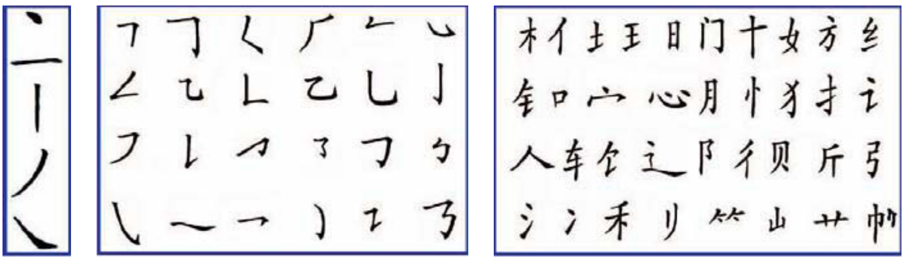


(a)



(b)

Fig. 8.3. (a) Hierarchical representation of a Chinese character (only four levels are shown); (b) Six-level hierarchical representation of calligraphy



(a) (b) (c)

Fig. 8.4. (a) Five primitive strokes; (b) 24 compound strokes; (c) 36 radicals

artwork (Fig. 8.3(b)). The "image" of the artwork will be rendered as the regions in the image space that are covered by the constructive ellipses. This representation is inspired by the Blum model [Blu67], in which a zonary area is defined through an ellipse moving along a predefined curve. Each constructive ellipse is parameterized by a 4×1 matrix, in which two rows store the coordinates of the constructive ellipse's center and the other two rows store the lengths of the major and minor axes of the ellipse. When we traverse the hierarchy from bottom up, such constructive ellipses are first "lined" up to form "primitive strokes" (Level 1). Then primitive strokes are combined to form "compound strokes" (Level 2) and subsequently to radicals (Level 3). Shape grammar rules are used for the composition (see Sect. 8.5.2). By grouping radicals based on their spatial proximity, characters are formed (Level 4). The learned examples of the same character in different styles will be blended together to establish a flexible model of that character in the model creation step (see Sect. 8.6). Finally, at Level 5, there is the top-level constructive element, a calligraphy artwork, which may consist of more than one character.

8.4.3 Advantages of Our Representation

(1) Reasoning from a set of existent calligraphy styles to generate new writing styles belongs to the hard domain of qualitative reasoning. Our parametric representation offers a tool to attack the challenging qualitative reasoning problem through quantitative means—analogous reasoning together with aesthetic constraint satisfaction—to be described in the sequel.
(2) With the hierarchical representation, our intelligent system allows efficient local learning of constructive elements, and the huge global knowledge representation space is reduced to one characterizing only local shape variations. Besides, the hierarchical nature of our representation supports efficient retrieval (and thus reuse) of past calligraphic artwork reasoning results (to be described in the sequel) at different representation levels.
(3) With our hierarchical parametric representation, calligraphy in all styles, including the very cursive ones which are heavily deformed and distorted, can be represented in a uniform six-level hierarchy and processed using the same reasoning pipeline. This increases our system's capability to learn and generate cursive calligraphy, which is a very important aspect of aesthetic calligraphy and a hot area for calligraphy artists.

8.5 Calligraphic Shape Decomposition

This is the process in which the hierarchical and parametric representations are extracted from training examples—images of calligraphic artwork.

8.5.1 Extracting Levels 0–1 Elements

To extract primitive strokes and thus the corresponding constructive ellipses from a training example, we first compute the skeleton of the input image, that is to compute a close approximation to the actual trajectory of the brush when the calligraphic artwork was created. Various approaches have been proposed for skeletonizing binary images of characters. We employed the algorithm proposed in [HY00], where the extracted skeleton is composed of segmented *primitive strokes*. Fig. 8.5 gives a step-by-step illustration. Such a stroke decomposition is by no means optimal, and our system can benefit from any improved decomposition algorithm.[1] Once the skeletons of the primitive strokes are identified, all the constructive ellipses can be computed efficiently using the Bresenham ellipse rasterization algorithm.

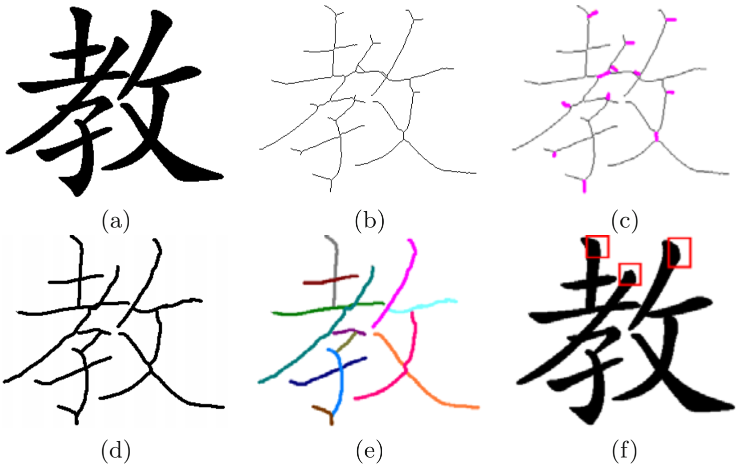


Fig. 8.5. Extracting Levels 0-1 elements of a character from its image: (a) The input image of a character, (b) the raw skeleton computed using a thinning algorithm, (c) the plausible short branches detected and color marked, (d) the short branches identified and removed, (e) the skeleton segmented into different strokes in the character and color coded, and (f) the reconstructed character using the extracted Levels 0-1 elements. Note that the reconstructed image (f) and the original image (a) have some slight differences at the ends of some of the strokes, e.g. areas indicated by the red rectangles

8.5.2 Extracting Levels 2–3 Elements

We identify compound strokes and radicals by analyzing the spatial relation between the primitive and compound strokes, respectively, through carefully designed shape grammar production rules. The syntactic description of any

[1] To further enhance the robustness of the stroke identification step, several structural variants of the five primitive strokes (Fig. 8.4) were used.

constructive element is represented using the syntax of the production system and generated by rule deduction. As an example, the shape production rule for the compound stroke in the upper leftmost corner of Fig. 8.4(b), denoted as $\mathbf{CS}_1$, is as follows:

IF horizontal($\mathbf{a}$) AND vertical($\mathbf{b}$) AND ontop($\mathbf{a,b}$) AND onleft($\mathbf{a,b}$) AND touch($\mathbf{a,b}$)
THEN $\mathsf{CS}_1 := \{\mathbf{a},\mathbf{b}\}$,

where horizontal($\mathbf{a}$), vertical($\mathbf{b}$), ontop($\mathbf{a,b}$), onleft($\mathbf{a,b}$) and touch($\mathbf{a,b}$) are the predicates indicating the relationships of horizontal primitive stroke, vertical primitive stroke, $\mathbf{a}$ on top of $\mathbf{b}$, $\mathbf{a}$ on left side of $\mathbf{b}$ and $\{\mathbf{a,b}\}$ touching each other, respectively.

To increase the reliability of the extraction process, we make use of fuzzy set theory as in [LHS98] so that a confidence value will be associated with each shape grammar production rule via the deduction process. The overall confidence of the shape grammar production can be derived by the confidences of all its statements. The rule that yields the highest overall confidence will be applied for the corresponding stroke composition.

8.5.3 Extracting Level 4 Elements

To extract the constructive elements at Level 4, we need to determine the radicals that can be grouped together to form a character. This is equivalent to the well-known problem of "character segmentation" in the pattern recognition field. In our system we use the standard projection analysis as in [YS94] to segment the individual characters in a calligraphy artwork.

8.6 Calligraphic Model Creation from Examples

8.6.1 Principles of Calligraphic Model Creation

To generate new calligraphic artwork, we apply an Analogous Reasoning Process (ARP) to a set of training examples of different calligraphic styles. The notion of generation/synthesis in artistic design was discussed by Simon [Sim75] in 1975. Keane [Kea88a] applied analogical mechanisms to problem solving. In general one can understand ARP as a process that synthesizes novel knowledge (shapes in our case) by fusing (blending in our case) together certain knowledge sources (the training examples). To support the fusion, establishing feature correspondence between the knowledge sources is needed.

In principle the ARP can be applied at different levels of the hierarchy, resulting in different artistic effects. Assume that the ARP is applied to $\mathbf{P}_{k,m}$, the m-th constructive element at the k-th level of the hierarchical representation and there are n different versions of $\mathbf{P}_{k,m}$: $\mathbf{P}^1_{k,m}, \cdots, \mathbf{P}^n_{k,m}$ derived from the n training examples, i.e., the independent knowledge sources in the ARP. The result of the ARP is denoted as $\mathbf{P}^r_{k,m}$. Then the general mathematical principle in the adopted ARP can be stated as:

$$\mathbf{P}^r_{k,m} = \sum_{i=1}^n \omega^i \mathbf{P}^i_{k,m}, \tag{8.1}$$

where ω^i $(i = 1, \cdots, n)$ is defined as the analogous reasoning intensity for $\mathbf{P}^i_{k,m}$ with the constraint that $\sum_{i=1}^n \omega^i = 1$. Obviously, $\mathbf{P}^i_{k,m}$ with a higher value of ω^i contributes more to the overall reasoning result.

The suggested ARP can be interpreted as either an interpolation or an extrapolation process. Note that here we assume a one-to-one correspondence among different versions of $\mathbf{P}_{k,m}$. In reality, a constructive element (a constructive ellipse, a primitive stroke, etc.) derived from a training example can correspond to one element in another training example in more than one way. A feature correspondence step (to be described in the next subsection) is therefore required before one can blend together features extracted from the different examples. In our intelligent calligraphy generation system, all the analogous reasoning intensities can be adjusted by the user manually through a graphical interface; or they can be generated randomly and fed to a subsequent phase that automatically filters out the ones violating some aesthetics-related constraints.

8.6.2 Fusing Knowledge Sources in ARP

To establish the feature correspondence between training examples for knowledge fusion, we first derive a discrete planar curve for each constructive element $\mathbf{P}^i_{k,m}$ using the centers of all the constructive ellipses associated with it. The curve forms the skeleton of the element, and critical points on the planar curves are detected using the algorithm in [ZC95] as the key points for setting up the correspondence.

In our application we first assume the shape of a constructive element in the font style "Kai" (GB2312) as used in the recent version of Microsoft Word to be the standard reference, which we denote as $\mathbf{P}^{\mathrm{std}}_{k,m}$. Note that because the shape of the element $\mathbf{P}_{k,m}$ has already been extracted in the shape decomposition phase, we can easily compute the deviation $\mathbf{F}^i_{k,m}$ by which the shape of the i-th source $\mathbf{P}^i_{k,m}$ differs from that of $\mathbf{P}^{\mathrm{std}}_{k,m}$ through applying the shape difference operator $\ominus$. The exact definition of this operator will be provided and explained in detail in the next chapter.

$$\mathbf{F}^i_{k,m} \triangleq \mathbf{P}^i_{k,m} \ominus \mathbf{P}^{\mathrm{std}}_{k,m} \tag{8.2}$$

With all the deviations of the reasoning sources $\mathbf{F}^1_{k,m}, \cdots, \mathbf{F}^n_{k,m}$ computed, we can then derive the overall deviation $\mathbf{F}^{\mathrm{r}}_{k,m}$, as follows:

$$\mathbf{F}^{\mathrm{r}}_{k,m} = \oslash(\mathbf{F}^1_{k,m}, \cdots, \mathbf{F}^n_{k,m}, \overline{\omega}), \tag{8.3}$$

where $\oslash$ is defined as the analogous reasoning mechanism simulation operator, which is currently implemented as an interpolation/extrapolation process in our prototype system. $\overline{\omega}$ is the *aesthetic viewpoint sequence* dictating the weights and order of the contributions from different sources. The ordered set of the intensities forms what is called the "viewpoint sequence" of the ARP. So not only will different reasoning intensities affect the final output, but different orders of presenting the training examples will also lead to different calligraphy results.

Finally, by adding back the shape of $\mathbf{P}^{\mathrm{std}}_{k,m}$, the standard constructive element associated with the reasoning result $\mathbf{P}^{\mathrm{r}}_{k,m}$ in the ARP, we obtain:

$$\mathbf{P}^{\mathrm{r}}_{k,m} = \mathbf{F}^{\mathrm{r}}_{k,m} \oplus \mathbf{P}^{\mathrm{std}}_{k,m}, \tag{8.4}$$

where the operator $\oplus$ is a reverse function of the operator $\ominus$.

Note that the ARP can be applied not only to the constructive elements from all the reasoning sources, but also to some topological constructors (in the form of geometric transformation matrices for the corresponding constructive elements) in order to further increase the reasoning power. Some simple ARP simulation operators for the topological constructors include arithmetic mean, geometric mean and harmonic mean.

8.6.3 A Computational Psychology Perspective

If all the intensities of the knowledge sources fall within $(0, 1)$, the ARP is in fact simulated using an interpolation process; otherwise it is simulated using an extrapolation process. From a psychological point of view, the existence of negative values for the reasoning intensities reflects the inverse reasoning of brain activities with certain input source knowledge being treated as negative examples. On the contrary, positive values correspond to exaggeration of brain activities where the larger an input example's reasoning intensity is, the more heavily the generated result will follow the style of that input source knowledge. When the number of knowledge sources is greater than two, the ARP mimics combined thinking activity, which will make use of several knowledge reference cases during the reasoning process.

8.7 Generating Artistic Calligraphy

With the mechanisms we describe above in place, candidates of novel calligraphic artwork can easily be generated by random perturbations of the reasoning intensities. As the analogous reasoning steps can be applied to something as fine as one single parameter of a constructive ellipse or something as coarse as all the parameters of a character, we have a highly flexible system to vary the shapes and generate many possible candidates. We describe next a filtering step to make sure that only the candidates which meet some aesthetic requirements would be output. The requirements would come from the training examples.

8.7.1 Extracting Aesthetic Constraints from Training Examples

Aesthetic constraints are criteria by which the aesthetic quality of a candidate or its parts is to be quantified and measured. They are categorized as:

1) constraints for visual appearance of a constructive element, and 2) constraints for spatial relationship between neighboring constructive elements. Fortunately the proposed ARP can automatically guarantee the satisfaction of the former one (at least under most circumstances) due to the parametric nature of the constructive elements. Therefore we only need to focus on deriving and applying constraints of the second type to guarantee the generation of visually pleasant novel calligraphy.

An important consideration for a quantifiable constraint on aesthetics is the *degree of overlapping* between two constructive elements. Three types of overlapping between a pair of elements, **a** and **b**, are used in our system: the x dimensional overlapping $\vartheta_x(\mathbf{a}, \mathbf{b})$, the y dimensional overlapping $\vartheta_y(\mathbf{a}, \mathbf{b})$, and the area overlapping $\vartheta_s(\mathbf{a}, \mathbf{b})$. All three measures are computed based on the bounding boxes of the constructive elements. After the overlapping measures are computed for all the element pairs of the training examples, their upper and lower bounds are recorded. The upper bound is used to avoid two neighboring elements within a newly generated calligraphy artwork being squeezed together while the lower bound is to avoid the neighboring elements being too far apart. These overlapping measures are then used to direct the process of generating the upper-level constructive elements from the lower-level ones. The overall effect is to constrain the ARP so that it will not perturb too much the spatial relationships of the *sub-components* of each constructive element as they are found in the training examples. Thus, for example, if a newly generated calligraphy candidate from the ARP, contains some sub-constructive elements whose x dimensional overlapping is smaller than the derived lower bound, the calligraphy candidates will be rejected.

If needed, the upper and lower bound constraints of the ARP can be relaxed in order to allow for results of new styles that cannot be easily imagined. In our system the end user can interactively adjust these two bounds according to his/her preferences. Thus, choosing the best values for the two bounds becomes a matter of the reviewer's personal aesthetic taste. According to the experience of using the proposed system, relaxing or ignoring the constraints in our analogous reasoning process seems to correspond to the creation of a more cursive and running style writing. Further study on the psychological analogy of the above computational simulation should be an interesting future research direction (see Sect. 8.10.1).

8.7.2 Past Results Reuse for Efficient Reasoning

While the ARP can be simulated by a random process which could be computationally intensive, reuse of similar past reasoning results (as experience) can be incorporated to make the reasoning process more efficient. In addition, the hierarchical representation allows a whole or partial "experience" to be reused. Our proposed system therefore proposes a high degree of reusability of past reasoning results.

8.8 Experiment Results

Fig. 8.6 shows the results obtained by our prototype system based on six training examples as the input knowledge sources and linear interpolation is used to simulate the generation step of the proposed analogous reasoning process. Fig. 8.7 shows the results of using five training examples and a non-linear interpolation process. Fig. 8.8 shows another set of results. It can be

Fig. 8.6. A single character in many styles; the first row is the training examples, and the other rows are automatically generated by our system

easily observed that there is consistency in style among characters within the same newly-generated calligraphic piece.

The results we obtained demonstrate that our approach can yield novel calligraphy styles given some existing ones. To verify that the system was indeed able to generate quality outputs, we asked practicing artists, art school professors and amateurs to examine the outputs; most of them considered our generated calligraphy to be acceptable. In addition, we have also analyzed the sensitivity in terms of the "creativity" of the system when the number of training examples is varied. The experiment was done using training examples with a varying number of styles which include "Kai", "Li", "Xingshu", "Weibei", "Xingkai", "Xingchao", and "Kuangchao". We invited six calligraphic fans with at least more than 2 years' writing experience and four professional calligraphists to form a review committee. They cast votes on the calligraphic artwork generated by the system. If an artwork received more than seven votes, it was considered a new calligraphic work. With more training examples of different styles, the chance of generating a creative and yet aesthetically acceptable calligraphy pieces increases. Also, between linear and non-linear APR, the latter is found to be able to generate more creative calligraphy pieces. Using 6 or 7 training examples, the linear ARP generated about 30 acceptable pieces of calligraphy, and the non-linear ARP generated more than 50.

We also analyzed the sensitivity in terms of the increase in creativity of the system when the number of learned samples was varied. Fig. 8.9 reports the results, where the sample styles learned are the shapes of the "Kai",

Fig. 8.7. A "couple" in many styles. (a) Training examples; (b)—(k) Some selected computer generated results

"Li", "Xingshu", "Weibei", "Xingkai", "Xingchao", and "Kuangchao" styles. We invited six calligraphic fans with at least more than 2 years' writing experience and four professional calligraphists to form a review committee, including a professor major in calligraphy in an art school. They cast votes on the calligraphic artwork generated by the system. If an artwork received more than seven votes, it was considered a new calligraphic work. Fig. 8.9 clearly shows that with more learned samples, the chance of generating an acceptable calligraphic piece increases.

Fig. 8.10 presents an interesting example. The calligraphy (the character "forever" in Chinese) in the top of the picture was generated fully automatically using our prototype system. The horse was generated through human manipulation using paint-brush software [XTLP04]. The character is in a rapid-running style that is in the same spirit as that of the running horse. Without the use of the proposed intelligent system, generating a piece of calligraphy that would match perfectly the painting is almost impossible.

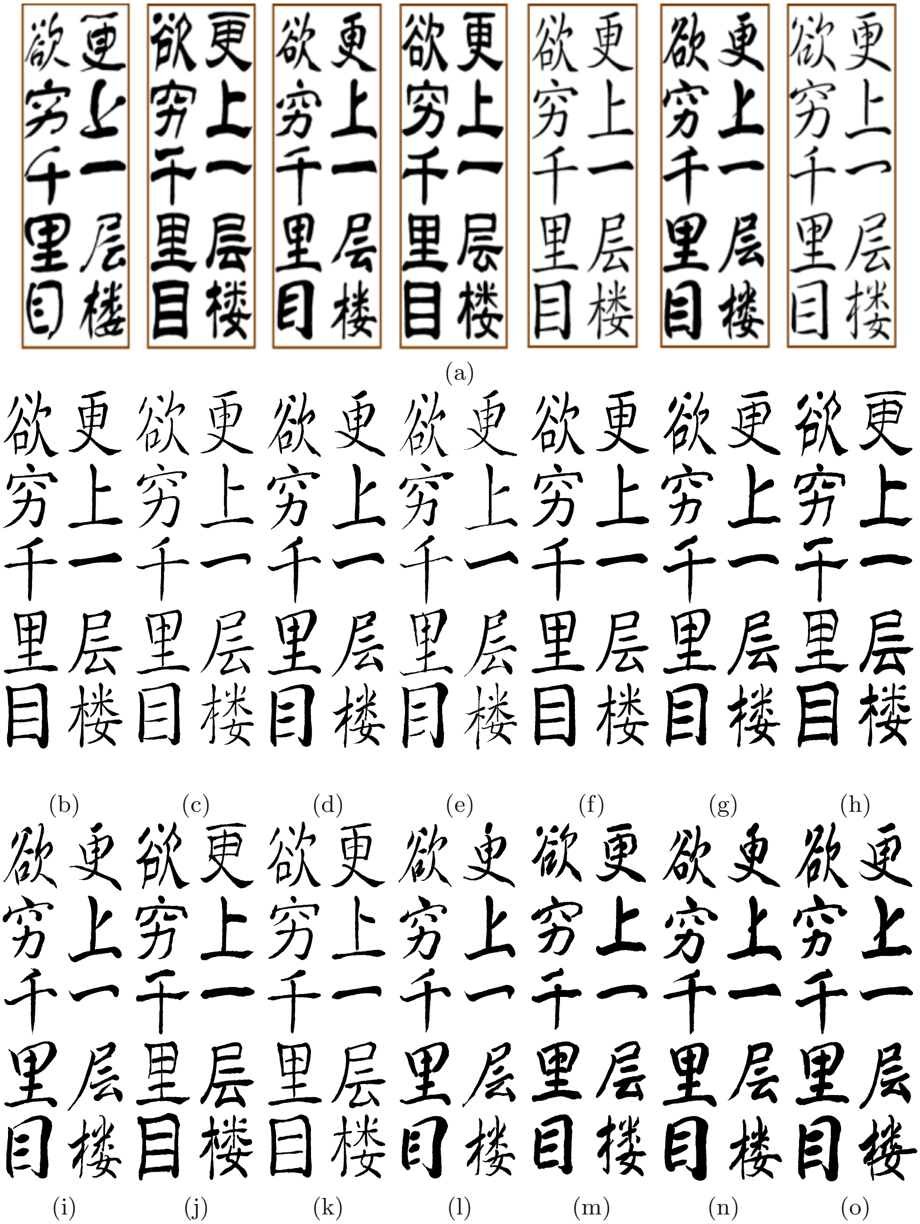
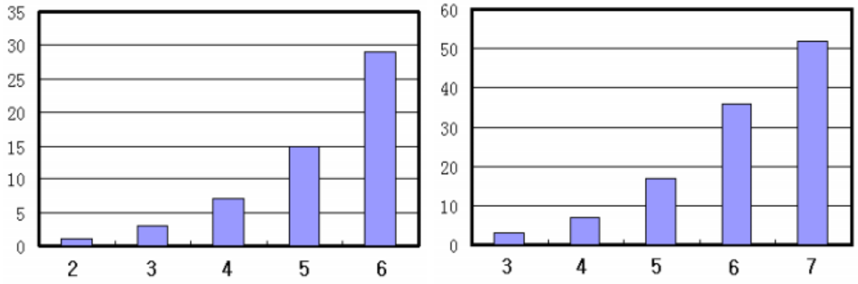


Fig. 8.8. (a) Learned samples in seven styles. (b to o) Some selected samples of newly-generated calligraphy



(a) (b)

Fig. 8.9. System's creativity (vertical axis—number of acceptable results) against number of learned samples (horizontal axis) (a) Single-character level using linear reasoning (b) Single-character level using non-linear reasoning

Fig. 8.10. "Forever running"

8.9 Possible Applications

The system described in this chapter is an innovative and yet practical system for generating novel Chinese calligraphy. Its effectiveness has been rigorously tested with satisfactory results. Computer-generated novel artistic calligraphy has the following potential applications.

(1) **Personalized font generation**. By importing the fonts installed in a computer, our proposed system can first compute each character of a flexible model by aligning all the corresponding characters of the different fonts. Then the system can ask for a small set of characters written by the users as additional knowledge. Based on these knowledge sources, the proposed ARP is simulated but now with the additional criterion to best match the user inputs. Because of the uniformity of the chosen hierarchical representation, the resulting set of intensities can be directly applied to the full character set of all the existing fonts, resulting in a font customized to the user's *handwriting.* We performed a simple test—the results are shown in Fig. 8.11. The top row shows the user's handwritten input characters and the ones below are generated by mimicking the writing style of the input. The results are surprisingly impressive. Of course, if the user's handwriting is so peculiar and unique that it lies outside the feasible space composed from all the existing fonts, the proposed system may still fail.

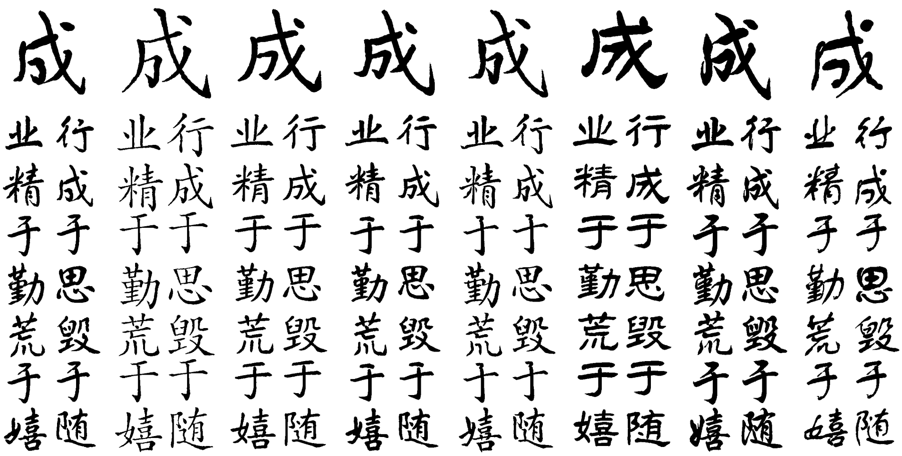


Fig. 8.11. Results of automatic handwriting style mimicking and calligraphy generation using the learned writing style from a single character: the first row of bigger characters are single characters written by different users in their respective handwriting styles, and the other rows are the automatically mimicked characters using the corresponding captured handwriting style

(2) **Handwriting beautification.** Handwriting is considered an important factor affecting people's impression of the writer. In many places, espe-

cially in Asia, handwriting is looked on as something that reflects the quality of a person. It is something like a speaking tone and accent in western society. To improve on one's handwriting could take a long time, which many VIPs often suffer by taking long hours of intensive and expensive personal coaching on handwriting during their own limited free-time. In situations where personal handwriting is preferred, our system can provide beautification of a person's handwriting. Our system can be applied to beautify people's handwriting. For instance, the user first writes his own handwriting, which is input as one source for the ARP. He then specifies some existing aesthetically appealing writing styles as the other sources. By manually setting the reasoning intensities, he can choose the extent to which his personal handwriting would be rectified, while at the same time preserving some degree of his original personal handwriting style. The computer can remember the setting, and so in the future he can always generate his beautiful handwriting with the same consistent style. A preliminary market survey has revealed a strong welcome for handwriting software with such a functionality.

(3) **Handwriting recognition.** Artistic calligraphy tends to contain many distorted characters. Normal Optical Character Recognition (OCR) techniques cannot effectively deal with them because they are mostly based on templates of styles that are commonly used.

However, each person is likely to have his own personal handwriting style. Thus there are countless different styles in the world. With our system, a relationship between the shapes of the same character written in different styles can be established. Such a relationship between even a small number of typical handwriting styles would allow the shapes of the character in a wide range of styles to be predicted by the system. This mechanism can be used in a calligraphy recognition system.

The proposed system is essentially a specific version of a deformable model for modeling Chinese characters of different calligraphic styles. The representation power and yet visually appealing properties of the adopted model makes it suitable for deformable model based handwriting recognition [CYC98]. In addition, the modeling approach based on the unified ARP is an excellent candidate for writer adaptation in related handwriting recognition systems.

(4) **A Chinese CAPTCHA agent.** The CAPTCHA project at Carnegie Mellon University (http://www.captcha.net) presents a good case for possible adoption of our approach. A Chinese CAPTCHA agent can be developed to avoid web sites crawling with software robots. The agent would generate heavily distorted Chinese writings which are readable by humans but not by any machine-computable algorithm.

8.10 Conclusion and Future Work

8.10.1 Conclusion

In this chapter our thesis has been that with the parametric hierarchical knowledge representation of Chinese calligraphy, the computer is able to create new Chinese calligraphic artwork in a variety of styles fully automatically and in real time based on a compact set of printed calligraphic inputs. The creativity capability of the proposed intelligent calligraphy generation system is mainly due to the huge feasible space available for the simulated analogous reasoning process. The experiment results show that our approach can indeed generate calligraphic artwork that can stand among existing ones, regardless of whether they appear to be realistic or completely inventive.

8.10.2 Future Work

There are a number of possible extensions to our proposed system. Some immediate future extensions to our proposed system include: 1) extending our approach to cover other languages; 2) adding a feedback component to be used to fine tune the aesthetic constraints through reinforcement learning; 3) capturing and translating the "psychological" states of other media so that they can be linked to the corresponding states in calligraphy, and therefore letting one use music to direct the generation of calligraphy.

Although we focus on automatic generation of Chinese calligraphy in this chapter, the lure and challenge of automatic generation of artistic calligraphy should not be limited to the Chinese language. See Fig. 8.1 (b), where artistic English and Arabic numerals are also used. So an immediate future work item would be to extend our algorithm to cover calligraphy in more languages. Another future direction is to add a feedback component behind the constraint satisfaction component to automatically tune for the best thresholds to be used in the constraint satisfaction. The tuning can be based on the evaluation marks given by human reviewers on the visual quality of the automatically generated calligraphy. This backward reinforcement mechanism can make our system more able to cater to the personal aesthetic taste of the reviewers. Further improvement of the constraint types, and different tolerances for different parts acquired either via training examples , or prior knowledge about Chinese characters, may also improve our system's performance.

There is a tradeoff between the creativity and the practical acceptability of interpolation results. Too strict a set of constraints could limit the creativity, while too loose a set of constraints could harm the overall acceptability of the results. How to find the best tradeoff point should be a worthwhile future pursuit.

Another interesting extension of this project is to explore the relationship between the "psychological" state and the "creativity" as possessed by the different simulated analogous reasoning processes. We can call this "quantitative aesthetics". If such a relationship can be established for not only calligraphy but also other computer synthesized creative works, e.g. computer music, then there could emerge the possibility of an intelligent multimedia application that couples the "psychological" states of the two media; that is, the style of the aesthetic fonts generated by our system can be dynamically changed according to music being played and the mood of human beings. In such an application, the rhythm and the spiritual content of a piece of music are expected to be automatically associated with artistic fonts carrying the same spiritual interpretations. Such a bridge between audio and visual expressions based on their psychological contents could in turn contribute to a better understanding of the artistic thinking of human beings.

The input calligraphic artwork samples we used are in different well-disciplined styles in the Chinese calligraphy world, based on which our system can produce a large number of new writing styles. How to create a new writing style with a pre-specified constraint on its style (as opposed to a character) is a much harder and more challenging research issue. In order to solve the problem, we need to extract the relationships between the parameters driving the analogy; these parameters include the analogous reasoning's source intensities and quantitative definitions for the visual features of different writing styles. The degree of automation to which our system can learn the sample source knowledge from copybooks can be further improved, which is a non-trivial pattern recognition problem for characters in cursive writing style.

Another exciting direction is "quantitative aesthetics". Every piece of newly created calligraphic artwork has a set of source intensities associated with the reasoning. Some generated results are more beautiful than others. The task is to find out the relationships among these source intensities and how they translate into aesthetic values. This may develop into a very fundamental topic in computational cognition. We will present some of our preliminary attempts to quantitative aesthetics research in Chapter 10.

References

[Blu67] Harry Blum. A transformation for extracting new descriptors of shape. *Models for the Perception of Speech and Visual Form,* (ed. Wathen-Dunn, W.), 10(2):362–380, 1967.

[Chu90] Yap S. Chua. Bézier brushstrokes. *Computer-Aided Design*, 22(9): 556–573, 1990.

[CYC98] Kwok-Wai Cheung, Dit-Yan Yeung, and Roland T. Chin. A Bayesian framework for deformable pattern recognition with application to handwritten character recognition. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 20(12):1382–1388, 1998.

[HY00] Rong He and Hong Yan. Stroke extraction as pre-processing step to improve thinning results of Chinese characters. *Pattern Recogn. Lett.*, 21(8):817–825, 2000.

[Kea88a] Mark Keane. Analogical mechanisms. *Artificial Intelligence Review*, 2(4):229–250, 1988.

[Knu79] Donald E. Knuth. *Tex and Metafont: New Directions in Typesetting.* American Mathematical Society, and Bedford, MA, USA: Digital Press, Providence, RI, 1979.

[LHS98] H.M. Lee, C.W. Huang, and C.C. Sheu. A fuzzy rule-based system for handwritten Chinese characters recognition based on radical extraction. *Fuzzy Sets and Systems*, 100(1–3):59–70, 1998.

[NTN93] Tomoyuki Nishita, Shinichi Takita, and Eihachiro Nakamae. A display algorithm of brush strokes using Bézier functions. In *CGI'93*: *Proceedings of CG International*, Lausanne, Switzerland: Springer-Verlag, pages 244–257, 1993.

[PMZS97] Zhigeng Pan, Xiaohu Ma, Mingmin Zhang, and Jiaoying Shi. Chinese font composition method based on algebraic system of geometric shapes. *Computers and Graphics*, 21(3):321–328, 1997.

[RG94] Geber Ramalho and Jean-Gabriel Ganascia. Simulating creativity in jazz performance. In *AAAI '94: Proceedings of the Twelfth National Conference on Artificial Intelligence*, Menlo Park, CA, USA: American Association for Artificial Intelligence, volume 1, pages 108–113, 1994.

[Sim75] Herbert A. Simon. Style in design. *Spatial Synthesis in Computer-Aided Building Design*, ed. Charles M. Eastman, pages 287–309, 1975.

[Str86] Steve Strassmann. Hairy brushes. In *SIGGRAPH '86: Proceedings of the 13th Annual Conference on Computer Graphics and Interactive Techniques*, Dallas, TX, USA: ACM Press, pages 225–232, 1986.

[XTLP02] Songhua Xu, Min Tang, Francis C.M. Lau, and Yunhe Pan. A solid model based virtual hairy brush. *Computer Graphics Forum (Proceedings of Eurographics '02)*, 21(3):299–308 & 625, 2002.

[XTLP04] Songhua Xu, Min Tang, Francis C.M. Lau, and Yunhe Pan. Virtual hairy brush for painterly rendering. *Graphical Models*, 66(5):263–302, 2004.

[YS94] Berrin A. Yanikoglu and Peter A. Sandon. Recognizing off-line cursive handwriting. In *Proc. Computer Vision and Pattern Recognition*, Seattle, WA, USA: IEEE Computer Society, pages 397–403, 1994.

[ZC95] Pengfei Zhu and Paul M. Chirlian. On critical point detection of digital shapes. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 17(8):737–748, 1995.