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Automatic Generation of Personal Chinese Handwriting by Capturing the Characteristics of Personal Handwriting

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Abstract

Personal handwritings can add colors to human communication. Handwriting, however, takes more time and is less favored than typing in the digital age. In this paper we propose an intelligent algorithm which can generate imitations of Chinese handwriting by a person requiring only a very small set of training characters written by the person. Our method first decomposes the sample Chinese handwriting characters into a hierarchy of reusable components, called character components. During handwriting generation, the algorithm tries and compares different possible ways to compose the target character. The likeliness of a given personal handwriting generation result is evaluated according to the captured characteristics of the person's handwriting. We then find among all the candidate generation results an optimal one which can maximize a likeliness estimation. Experiment results show that our algorithm works reasonably well in the majority of the cases and sometimes remarkably well, which was verified through comparison with the groundtruth data and by a small scale user survey.

Introduction

Personal handwriting can bring writers closer to the readers than texts printed in a standard font. However, handwriting is less preferred than typing in the digital age—being more time consuming is one of the reasons. It is therefore meaningful to develop an algorithm to automatically generate personal handwritings in any person's writing style. In this paper, we propose such an intelligent algorithm for Chinese writers. After seeing a small set of an arbitrary writer's sample writings in Chinese, our algorithm is able to generate personal handwritings in that writer's personal writing style.

The problem of automatic generation of personal Chinese handwriting is challenging because Chinese characters have large shape variations at the stroke level, and the spatial relationships between individual strokes within a character can be highly sophisticated. The rich variation in the style of Chinese handwriting and the diversity of Chinese character composition give Chinese calligraphic art a high aesthetic value, thus attracting many art fans. We present our solution to this difficult problem in this paper.

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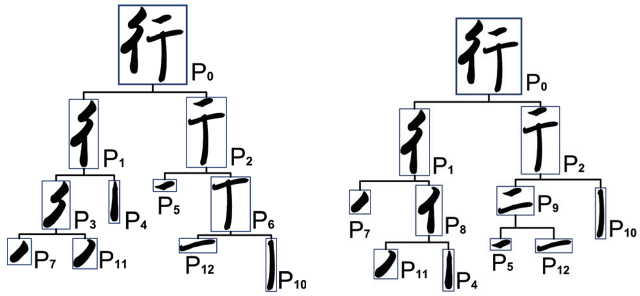
In addition to automating the task of handwriting Chinese characters, the intelligent algorithm we propose in this paper can have many other interesting and practical applications. For example, we can use the algorithm to build a personalized font by asking the person to write out a small subset of the Chinese characters. Another meaningful application would be to mimic the handwritings of famous calligraphists, the results of which could be useful in design, decoration, advertisement, etc. Also automatically generating one's personal handwriting may provide additional reference materials for handwriting forgery detection: By feeding all the available writing samples of a person to the algorithm, the algorithm can generate a best imitation of the person's handwriting over any piece of given text; the generated result can then be compared with the suspected handwriting to determine if the latter might be faked or not.

Hierarchic Structure of Chinese Characters

The shapes of Chinese characters can usually be represented by a tree structure building upon a few most basic constructive elements. Figure 1 shows one example of a Chinese character composed of several constructive elements (abbreviated as "character elements" or simply "elements").

The hierarchical structure of Chinese character composition makes shape grammar a suitable choice for representing the structure. We augment shape grammar with writer specific information to capture the characteristics of personal handwriting. The augmented shape grammar is then applied to generating personal Chinese handwriting through a learning based approach. Initial experiments have produced very promising results.

The structure of the rest of this paper is as follows. We first discuss how to generate handwriting Chinese characters using shape grammar, and then look at how to capture the characteristics of Chinese handwriting using augmented shape grammar. After that we explain how to evaluate the likeliness of a personal Chinese handwriting generation result via augmented shape grammar, and our approach to generating personal handwriting through finding a candidate result which can optimize the likeliness estimation. We then report some experiment results, which is followed by a discussion on related prior studies. Finally, we conclude the paper.



(a) (b)

Figure 1: The hierarchical representation of a Chinese character where (a) and (b) present two possible ways of composition.

$$
\begin{array}{llcl}
Rule_1 & P_0 & = & (\textsf{left\_notouch}\ P_1, P_2) \\
Rule_2 & P_1 & = & (\textsf{up\_touch}\ P_3, P_4) \\
Rule_3 & P_2 & = & (\textsf{up\_notouch}\ P_5, P_6) \\
Rule_4 & P_1 & = & (\textsf{up\_notouch}\ P_7, P_8) \\
Rule_5 & P_2 & = & (\textsf{up\_touch}\ P_9, P_{10}) \\
Rule_6 & P_3 & = & (\textsf{up\_notouch}\ P_7, P_{11}) \\
Rule_7 & P_6 & = & (\textsf{up\_touch}\ P_{12}, P_{10}) \\
Rule_8 & P_8 & = & (\textsf{up\_touch}\ P_{11}, P_4) \\
Rule_9 & P_9 & = & (\textsf{up\_notouch}\ P_5, P_{12})
\end{array}
$$

Figure 2: Shape grammar rules useful for composing the character P_0 in Figure 1.

Generating Handwriting Chinese Characters via Shape Grammar

The shape of a Chinese character has a recursive representation. Figure 1 shows two possible ways to hierarchically form a Chinese character. Each way corresponds to one parsing path of the character in the shape grammar system. This property motivates us to choose shape grammar to guide the personal Chinese handwriting generation process.

Like any grammar system, a shape grammar system consists of a collection of shape production rules. The set of shape grammar rules relevant to the composition of the character P_0 in Figure 1 are shown in Figure 2. Each rule specifies how to compose a character element from lower-layer elements. Beside the character elements, another building block essential in our shape grammar system for representing handwriting Chinese characters is the *character composition predicate* (or just "predicate"). A predicate specifies the spatial relationship between character elements. For example, in $Rule_1$ in Figure 2, the predicate left_notouch means that P_1 stays on the left side of P_2 and they do not touch each other. In fact, Figure 1 illustrates how a character element is composed from several lower-layer elements following these shape grammar rules.

Applying these rules, we can systematically and exhaustively enumerate all the possible ways to compose the character P_0. Finding all these ways of composition is a key to our successful generation of personal Chinese handwriting, as personal handwriting generated from following some compositional ways tend to give better results, because not all the compositional ways are equally informed in terms of available handwriting samples. We will look at this issue more deeply later.

During the process to find all the possible ways to generate the shape of the character P_0, each constructive element, P, of the character is also associated with a type property $\tau(P)$, representing the type of the element according to the conventional Chinese character morphological formation categorization schema (Kirk, Sillars, and Hsu 1965). We will discuss how to determine the value of $\tau(P)$ later. Once the type property of a character element is known, we can generate the actual shape of P_0 as guided by the shape grammar system.

Capturing Characteristics of Personal Chinese Handwriting through Augmented Shape Grammar

In this section, we present the method to use augmented shape grammar to capture writer specific characteristics of personal handwriting, and the associated knowledge extraction techniques to instantiate a specific augmented shape grammar system for a certain writer.

Augmented Shape Grammar to Capture Writer Specific Characteristics of Personal Handwriting

The augmented shape grammar system is constructed by augmenting each individual shape grammar rule. The augmentation process consists of associating two kinds of writer related information with all the elements and predicates involved in each shape grammar rule: the probability ρ for each of them to be created by a certain writer and the associated confidence φ of each such estimation. Unlike the conventional shape grammar systems for representing Chinese character formation, which do not consider variation in personal handwriting styles for different writers, our augmented shape grammar system models the morphological formation of Chinese characters in a writer dependent way, taking into account personal biases.

Instantiating Augmented Shape Grammar for a Specific Writer

We now look at how to optimally instantiate our augmented shape grammar system for a specific writer X. The processing consists of determining a best set of probability and confidence values for all the character elements and character formation predicates for the writer, i.e., to optimally assign values to all the ρ's and φ's involved in the shape grammar system given a set of training samples of personal handwriting. To achieve this goal, we follow a learning based approach.

Determining writer specific information for character elements. Given an image of a character element Y, to determine $\rho_i(P, X, Y)$, i.e., the probability for the character element to be of type $\tau(P)$ and written by X, and also the associated confidence $\varphi_i(P, X, Y)$ of the above probability estimation, we take the following steps. First, we find in the training set all the character elements that are of the type $\tau(P)$. We then employ a fuzzy categorical data clustering algorithm (Kim, Lee, and Lee 2004) to solve the above problem. This fuzzy clustering algorithm outputs the clustering result in the form of a fuzzy number, indicating the likelihood that the element Y is created by the writer X. We assign this estimated likelihood as the $\rho_i(P, X, Y)$ value in our context. To derive $\varphi_i(P, X, Y)$, we first measure the performance of the clustering process using the traditional ten-fold cross validation technique. And the overall average categorization accuracy is treated as $\varphi_i(P, X, Y)$.

Determining writer specific information for character formation predicates. To instantiate our augmented shape grammar system to capture the characteristics of writer X's handwriting in Chinese, we also need to determine, given an observation of a spatial relationship between a few character elements, the probability and confidence for the demonstrated spatial relationship to correspond to a certain type of character formation predicate under X's personal handwriting style. Fortunately, this problem was well studied before as it is akin to optical character recognition of Chinese characters. Numerous papers have been published on this topic. In our work, we adopt the algorithm proposed in (Chang and Yan 1999) because of its ease of implementation and relatively robust performance. The output of the algorithm is a fuzzy number where each component of the number indicates the likelihood of the observed spatial relationship to correspond to a certain type of well defined character formation relationship. We output the likelihood for Y to correspond to the character formation type $\tau(\mathsf{R})$ and created by the writer X as $\rho(\mathsf{R}, P'_1, \cdots, P'_n, X, Y)$, where $P'_1, \cdots, P'_n$ are the character elements involved in the predicate. For the confidence of the above character formation predicate categorization estimate, we follow a similar approach to use the measured accuracy of the above relationship categorization process via a ten-fold cross validation as the value for $\varphi(\mathsf{R}, P'_1, \cdots, P'_n, X, Y)$.

Evaluating the Likeliness of Personal Handwriting through Augmented Shape Grammar

As mentioned at the beginning of this paper, the success of the generation of personal handwriting in Chinese rests upon an evaluation process which measures how likely a certain personal handwriting candidate result matches a given writer. We now look at the details of this evaluation method which is essentially realized using the augmented shape grammar system instantiated for a particular writer.

Propagate Writer Specific Information via a Neural Network based Approach

For an arbitrary shape grammar rule, $Rule_* : P = (\mathsf{R}\ P'_1, P'_2, \cdots, P'_l)$, while conducting the shape grammar deduction to compose the element P based on the lower level elements $P'_1, P'_2, \cdots, P'_l$ in the character formation hierarchy, we propagate also the writer's specific information, i.e., ρ's and φ's. We realize this processing via a neural network based approach. We introduce two classes of neural networks, one for propagating the confidence values φ's, which we denote as NN_φ, and the other for propagating the likelihood values ρ's, which we denote as NN_ρ. We assume $\varphi(P)$ is a function of all the $\varphi(P'_s, X, Y)$'s and $\rho(P)$ is a function of all the $\rho(P'_s, X, Y)$'s where $s = 1, \cdots, l$. That is, they are the functions of confidence values or probability values of all the lower level elements of P involved in the shape grammar deduction process to compose P. According to the assumption, the input to our neural network NN_φ includes $\varphi(\mathsf{R}, P'_1, \cdots, P'_l, X, Y)$ and $\varphi(P'_s, X, Y)$ $(s = 1, \cdots, l)$; and the input to NN_ρ includes $\rho(\mathsf{R}, P'_1, \cdots, P'_l, X, Y)$ and $\rho(P'_s, X, Y)$ $(s = 1, \cdots, l)$. The output of NN_φ is $\varphi(P, X, Y)$, while the output of NN_ρ is $\rho(P, X, Y)$. The type of neural network we use here is the classical back-propagation neural network.

To prepare the training examples, we find all the shape grammar rules in which all the involving character elements and character formation predicates have been previously written by the writer X. Hence all the φ and ρ terms involved in these shape grammar rules can be derived. For each such case, since the input and expected output of our neural network are known, they form a training sample for our neural network.

Using Augmented Shape Grammar to Optimally Estimate Personal Handwriting Likeliness

Given a candidate personal handwriting generation result Y, we can use our augmented shape grammar system to optimally estimate the likeliness of Y being an instance of writer X's handwriting for a certain character element P. To carry out this processing, first we find all the possible ways to compose P following a certain deduction path in the shape grammar system. We assume in total there are n possible paths to compose P using character elements in the lower levels of P in the character composition hierarchy. We denote these composition paths as $\mathbf{CP} \triangleq \{cp_1, cp_2, \cdots, cp_n\}$ respectively. We then derive the $\rho(cp_i)$ and $\varphi(cp_i)$ values for the situations where the character element P is composed by following the paths $cp_1, \cdots, cp_n$ respectively. After that, we define a combined measurement $O_{cp_i}(P, X, Y)$ on the overall likeliness of the handwriting sample Y being written by the writer X for the character component P following the composition path cp_i as follows:

$$O_{cp_i}(P, X, Y) \triangleq \rho(cp_i)\varphi(cp_i). \tag{1}$$

After $O_{cp_i}(P, X, Y)$ is computed for all the composition paths, we choose an optimal path cp_{opt} that maximizes $O_{cp_i}(P, X, Y)$, i.e., $cp_{\text{opt}} \triangleq \arg\max_{cp_i \in \mathbf{CP}} O_{cp_i}(P, X, Y)$. We then output the combined estimation score $O_{\text{est}}(P, X, Y) \triangleq O_{cp_{\text{opt}}}(P, X, Y)$ as our optimal likeliness estimation for the element Y being a written instance by the writer X for the character component P.

Generate Personal Handwriting via Likeliness Maximization

Once we can estimate the likeliness score for a candidate handwriting instance Y being true personal handwriting by the writer X for a certain element P (see (1)), we can then use an optimization process to generate a most likely handwriting result to approximate X's personal handwriting for the element P. More concretely, given a piece of Chinese text, we first generate some candidate handwriting result for the text using an existent Chinese handwriting generation algorithm (Xu et al. 2005). In this algorithm, a few free parameters (typically less than ten) are used to collectively specify the visual style of the generated handwriting for a character. This way of controlling the algorithm's behavior provides a good interface for our handwriting style mimicking algorithm—we can simply find an optimal setting for these free parameters to maximize our personal handwriting likeliness estimation. In our experiment, we apply the gradient descent algorithm to solve the optimization problem. Through this process, we can generate Chinese calligraphic writings character by character over the given text using the expected writer's personal handwriting style.

Experiment Results

We present results of several personal handwriting generation experiments in Figures 3–5. One can see that these generation results are indeed reasonably good approximations of the personal handwriting styles of the corresponding sample handwritings. For the generation experiment reported in Figure 4, we have conducted a small-scale quantitative user study to more objectively evaluate the quality of the generation results, in the form of a quasi Turing test. We invited eight educated Chinese individuals, denoted as A to H, to try to identify the generated personal handwritings by our algorithm and the authentic writings by a calligraphist. We first showed them 16 sample characters written by a calligraphist, and then 32 characters, and asked them to say which ones are written by the calligraphist and which ones are the facsimiled results by our algorithm. Table 1 shows the survey results with statistics on the accuracy. The columns from left to right respectively correspond to the test case number, the sub-figure number in Figure 4, the groundtruth result "Gd.", the human identification results by the persons A to H respectively, and the average accuracy of human identification (A-%). If a person thinks the character is generated by our algorithm, it is marked $\surd$, otherwise $\times$. Table 1 is sorted by the character number in Figure 4. In our user survey, the actual presentation sequence of these test cases was randomly determined. The best human judge achieves an overall accuracy of 65.6% while the poorest is 31.3%; the average accuracy over all these human judges is 50.8% for all the characters used in the experiment. Note that if a judge identifies these results via random guessing through coin tossing, the overall identification accuracy would be 50%. If we break down the overall average, the average accuracy of all the human judges is 59.2% for machine-generated characters, and 43.4% for human-generated characters. Even though the two accuracy figures differ to some extent, in the eyes of our panelists, our automatically generated characters under most of the situations appear very similar to the authentic ones in their personal handwriting style. Lastly, we also asked each of our panelists, for every character that he or she thought is a machine generated one, whether it appears to be

No.	Fig.	Gd.	A	B	C	D	E	F	G	H	A-%
1	(1)	×	×	√	√	√	√	√	√	√	12.5
2	(5)	×	√	√	×	√	×	√	√	√	25.0
3	(6)	×	×	√	√	√	√	×	×	√	37.5
4	(7)	×	√	√	×	√	×	×	√	√	37.5
5	(9)	×	×	√	√	×	×	√	×	×	62.5
6	(16)	×	×	√	√	√	√	√	×	√	25.0
7	(19)	×	×	√	√	×	√	×	√	√	37.5
8	(20)	×	×	√	×	×	×	√	×	×	75.0
9	(23)	×	×	√	×	×	√	√	×	√	50.0
10	(24)	×	×	×	√	×	√	×	×	√	62.5
11	(29)	×	×	√	√	√	√	√	×	√	25.0
12	(30)	×	×	√	√	√	√	√	√	√	12.5
13	(34)	×	×	×	×	×	×	√	×	√	75.0
14	(37)	×	√	×	×	√	√	√	√	√	25.0
15	(40)	×	×	√	√	×	√	√	×	√	37.5
16	(43)	×	×	√	×	×	×	√	×	√	62.5
17	(47)	×	×	√	×	×	×	√	×	×	75.0
18	(50)	√	×	√	×	×	×	×	×	×	12.5
19	(51)	√	√	√	√	×	√	√	√	√	87.5
20	(52)	√	×	√	×	√	√	√	×	×	50.0
21	(53)	√	×	√	×	×	√	√	×	×	37.5
22	(55)	√	×	√	√	√	√	×	√	√	75.0
23	(62)	√	×	√	√	√	×	×	√	√	62.5
24	(65)	√	×	√	×	√	×	×	√	√	50.0
25	(66)	√	×	√	√	√	×	×	×	√	50.0
26	(67)	√	×	×	√	√	×	√	√	√	62.5
27	(71)	√	√	√	√	√	√	×	×	√	75.0
28	(72)	√	√	√	×	√	√	×	√	√	75.0
29	(73)	√	×	×	√	√	√	×	×	√	50.0
30	(74)	√	×	√	×	√	√	×	√	√	62.5
31	(76)	√	√	√	×	√	×	√	×	√	62.5
32	(78)	√	√	√	√	√	×	√	×	√	75.0
A-% (1–17)			82.4	17.6	47.1	52.9	41.2	23.5	64.7	17.6	**43.4**
A-% (18–32)			33.3	86.6	53.3	80.0	53.3	40.0	46.7	80.0	**59.2**
A-% (1–32)			59.4	50.0	50.0	65.6	46.9	31.3	56.3	46.9	**50.8**

Table 1: The human identification results over our personal handwriting generation experiment results reported in Figure 4. Note that the judges saw these test cases in random order.

a well-written character regardless of the handwriting style. All of them commented that all the characters they had seen in the experiment, whether machine generated or not, were well-written.

To better understand the capability of our algorithm in automatically generating handwriting in personal writing style, we performed a controlled experiment where the generation likeliness maximization component is turned off. The results are shown in (31^*)–(44^*) in Figure 5, which are compared side by side with machine generation results when the component is enabled as well as with the authentic human handwriting results. According to our panel of judges, many of the character generation results such as (31^*), (32^*), (34^*), (35^*), (36^*), and (37^*) are not as pretty as the machine generation results when the likeliness maximization component is enabled. We assume the reason is because of the multiple ways to synthesize a character using strokes one has previously written; and with the augmented shape grammar

Figure 3: A personal handwriting generation experiment. (1)–(24) are 24 out of 40 characters written by a calligraphist, which are used as the training examples to instantiate the augmented shape grammar for capturing the characteristics of the calligraphist's handwriting style in this experiment. Characters (25)–(32) are personal handwriting results generated by our algorithm, which are compared with the authentic handwriting results shown in (25^{a})–(32^{a}).

guided generation likeliness maximization, a visually more appealing result is more likely to be found than without the maximization procedure.

Related Work

The work in (Xu et al. 2005) is most related to our work reported here. They use shape grammar to decompose Chinese characters in a hierarchical manner. But they did not augment the shape grammar to capture the characteristics in the shape formation of Chinese characters. People have also tried fuzzy methods, e.g., (Ozaki M. and Ishii 1992), to evaluate the quality of calligraphic writings. In these fuzzy methods, membership functions may be introduced to capture the handwriting styles of different calligraphists; however, the design of these membership functions is usually manually done and fixed once and for all. In comparison, our augmented shape grammar is dynamically trained on the fly when more sample characters written by the same calligraphist are observed by our algorithm. Through this on-line learning based functioning of our algorithm, we can capture the characteristics of individual's calligraphic handwriting flexibly and with ease.

Jawahar and Balasubramanian (2006) studied synthesis of Indian scripts in handwriting style. They employed a simple stroke and layout model and successfully facsimiled handwritings for multiple Indian languages. In contrast, we adopt a more elaborate stroke model to capture stroke shapes in Chinese calligraphic writings with high fidelity. Most recently, Xu et al. (2008) suggested a similar algorithm for synthesizing Chinese handwriting. Both algorithms, however, do not model the personal handwriting characteristics, i.e., the habitual variations of personal handwritings. In this paper, we introduce a statistical modeling method for capturing the characters of personal handwritings. Once the personal handwriting characteristics are captured, we feed them into the facsimileing pipeline. Also, via modeling the characteristics of personal handwritings, we can produce the most likely facsimile of a person's handwriting. Our algorithm presents a meaningful extension to these two prior algorithms.

Conclusion

In this paper, we augmented the classical shape grammar to capture the characteristics of individual writers' writings to facilitate the automatic creation of Chinese calligraphic handwriting. The augmented shape grammar system is instantiated through an on-line learning process for a specific individual writer. With the trained shape grammar system, we have achieved satisfactory experiment results in generating personal handwriting in Chinese.

Acknowledgments

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Figure 4: A personal handwriting generation experiment over a Chinese poem by the great Chinese poet Shu Shi (1037-1101). (1)–(48) are 48 out of 90 characters written by a modern calligraphist, which are used as training examples; characters (49)–(78) are facsimiled results by our algorithm; and characters (49^a)–(78^a) are the authentic handwriting by the calligraphist.

Figure 5: Another personal handwriting generation experiment. (1)–(30) are 30 out of 82 characters written by a modern calligraphist, which are used as training examples; characters (31)–(44) are the personal handwriting generation results by our algorithm, which are compared with the authentic handwriting by the calligraphist over these characters (31^a)–(44^a). For comparison purpose, (31^*)–(44^*) are machine generation results when the generation likeliness maximization component is turned off.