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Intelligent Evaluation Method of Calligraphy Characters Based on Deep Stroke Extraction

Meng Li[1,a,*], Guanghao Ren[1,b]

[1]Institute of Automation, Chinese Academy of Sciences, Beijing, China
[a]meng_li@ia.ac.cn, [b]guanghao.ren@ia.ac.cn
[*]Corresponding author

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Abstract: Calligraphy is an important part of Chinese culture. And calligraphy education is the main way to spread calligraphy culture. Intelligent calligraphy evaluation can reduce dependence on experienced calligraphy teachers and effectively enhance the development of calligraphy culture. However, traditional intelligent calligraphy evaluation methods mostly focus on the whole and lack fine-grained analysis, which cannot form effective evaluation results. In this paper, we propose an intelligent evaluation method for calligraphy characters based on deep stroke extraction. By disassembling calligraphy character strokes, a more fine-grained evaluation of the writing results of a single stroke can be achieved. This method consists of two main parts: stroke extraction module that extracts single strokes through a structure deformable image registration-based stroke extraction model; evaluation module that provides detailed quantitative evaluation results from the whole character, radicals and single strokes. The experimental results show that our method can extract strokes of complex calligraphy characters and provide detailed evaluation results of calligraphy characters effectively.

1. Introduction

Calligraphy copying is the main way to learn calligraphy. The intelligent copying evaluation method provides evaluation results by finding the writing differences between target calligraphy character and reference calligraphy character. The intelligent calligraphy character evaluation method is of great significance to the dissemination of calligraphy culture. And, it can also be used to support the automated analysis of ancient calligraphy characters.

Although intelligent calligraphy character evaluation is beneficial to many tasks, evaluating of calligraphy characters is always complex and difficult. By analyzing the characteristics of Calligraphy characters, it can be found that the difficulties of intelligent calligraphy character evaluation mainly include the following two aspects. First, calligraphy fonts are diverse and the number of characters is large. Many characters have complex structures, making their analysis difficult. Second, Evaluation methods are largely influenced by subjectivity and there is no unified evaluation standard. Which makes it more difficult to build an intelligent evaluation model that can adapt to multiple application scenarios.

Existing intelligent calligraphy character evaluation methods mostly focus on an overall perspective, or analyze strokes in specific scenarios. Although the existing methods have achieved good evaluation results, they cannot be applied in real calligraphy teaching. Existing methods have the following three drawbacks or constraints: (1) The method has relatively high environmental requirements and cannot adapt to real calligraphy learning scenarios. (2) The evaluation granularity is not fine enough, and there is a lack of evaluation of the details of calligraphy characters. (3) The evaluation method lacks analysis of the real evaluation process of calligraphy teaching.

To solve these problems, we propose an intelligent evaluation method for calligraphy characters based on deep stroke extraction. Efficient evaluation strategies are constructed by analyzing the real teaching process of calligraphy teachers. And through stroke extraction technology, our method can achieve multi-granularity evaluation of calligraphy character writing results. The method contains two main modules: stroke extraction module that extracts single strokes through a structure deformable image registration-based stroke extraction model; evaluation module that provides detailed quantitative evaluation results. Our main contributions are as follows.

(1) We propose an intelligent evaluation method for calligraphy character, which takes multiple calligraphy character granularities into consideration to achieve efficient and accurate evaluation of calligraphy characters.

(2) We propose an improved stroke extraction method. By strengthening the analysis of the overall characteristics of the stroke extraction process, the accuracy of calligraphy stroke extraction is improved.

2. Related Work

2.1. Calligraphy Evaluation

Calligraphy evaluation can be simply understood as evaluating the quality of writing. According to whether there is reference calligraphy characters, it can be divided roughly into two categories: template-free[1-3] and template-based[4-9]. Template-free methods mostly combine calligraphy writing experience and directly evaluate the writing quality based on the morphological features of calligraphy characters. Wang[1] classifies each stroke of calligraphy characters into five basic strokes and obtains evaluation results by analyzing whether each stroke conforms to the corresponding basic stroke. Xu[3] uses the calligraphy character skeleton to simply divide the calligraphy character radical areas and obtains the aesthetic evaluation results of the calligraphy characters by calculating the morphological relationships of different areas. The template-based method mainly calculates the difference between the target calligraphy image and the reference calligraphy image. Template-based methods are more suitable for calligraphy teaching scenarios. Wang[4] uses sensors to obtain motion data during the calligraphy writing process, and uses LSTM to calculate the feature differences between the target calligraphy images and the reference calligraphy images as evaluation results. Sun[9] calculated the overall calligraphy feature difference between the target calligraphy characters and the reference calligraphy characters, as well as the overall morphological feature differences at different angles, and combined the two differences as the evaluation results.

2.2. Stroke Extraction for Chinese Character

For most existing Chinese character stroke extraction methods, analyzing cross areas is the core and primary task. Sun[10] disassembled regular script characters into simple strokes for calligraphy robots by detecting corners caused by interlaced strokes. He[11] uses chain line segments to represent the boundaries of characters and separate interleaved strokes by detecting whether these boundaries are regular. To further improve the accuracy of stroke extraction, some template-based methods have been proposed[12,13]. Wang[13] use stroke structure matching to establish the correspondence between strokes and template strokes. However, this method lacks the utilization of prior knowledge. Li[12] proposed a stroke extraction method that combines semantics and prior knowledge, providing prior knowledge to written characters through image registration and achieving remarkable results. However, this method lacks analysis of the overall written character in the single stroke extraction part.

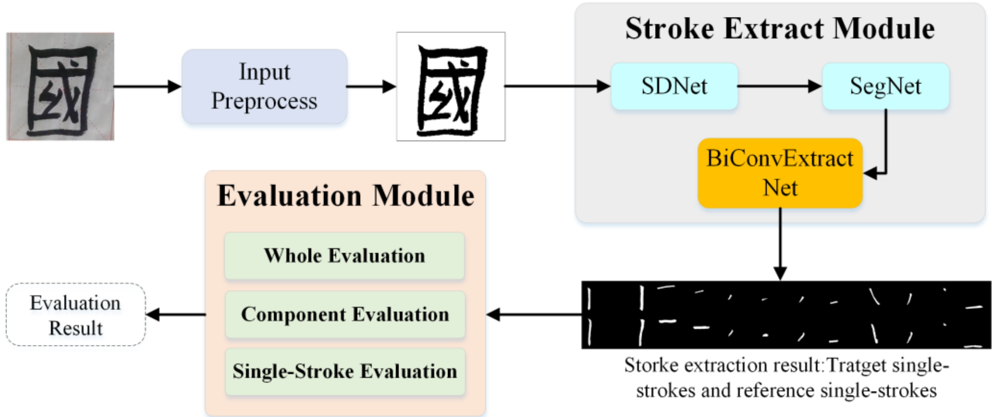

Figure 1: The pipeline of our method.

3. Method of Calligraphy Intelligent Evaluation

Our method of calligraphy intelligent evaluation proposed in this paper, shown in Figure 1, consists of two main modules. (1) The stroke extraction module obtains a single stroke of the target calligraphy character to prepare for evaluation. (2) The evaluation module for calligraphy character is used to evaluate calligraphy characters from multiple angles as a whole character, radicals, and single strokes to achieve multi-granularity and efficient evaluation results.

3.1. Stroke Extraction Module

We use the method in [12] as the main framework for stroke extraction, as shown in Figure 2. Considering that the third part of [12] for single stroke extraction lacks analysis of the entire stroke, we propose an optimized extraction method (BiConvExtractNet) based on bidirectional convolution LSTM[14,15] for single-stroke. By combining the features of different strokes, extraction errors in cross strokes can be eliminated. Improved the accuracy of calligraphy stroke extraction.

3.1.1. Structure of BiConvExtractNet

The structure of BiConvExtractNet is shown on the right side of Figure 2. The input is an image sequence composed of target image and reference single-stroke images. Each loop has four inputs: target image, segment result of target image, corresponding reference single-stroke image, and reference segment result. The size of all input are 256×256. First, the input data passes through a 4-layer Encoding network, and the input image is convolved down to 64×64. Then it continues to convolve down to 8×8 through an encoding bidirectional convolution LSTM, and convolves up to 64×64 through a decoding bidirectional convolution LSTM. Finally, the corresponding single-stroke extraction result is obtained through a 2-layer decoding network.

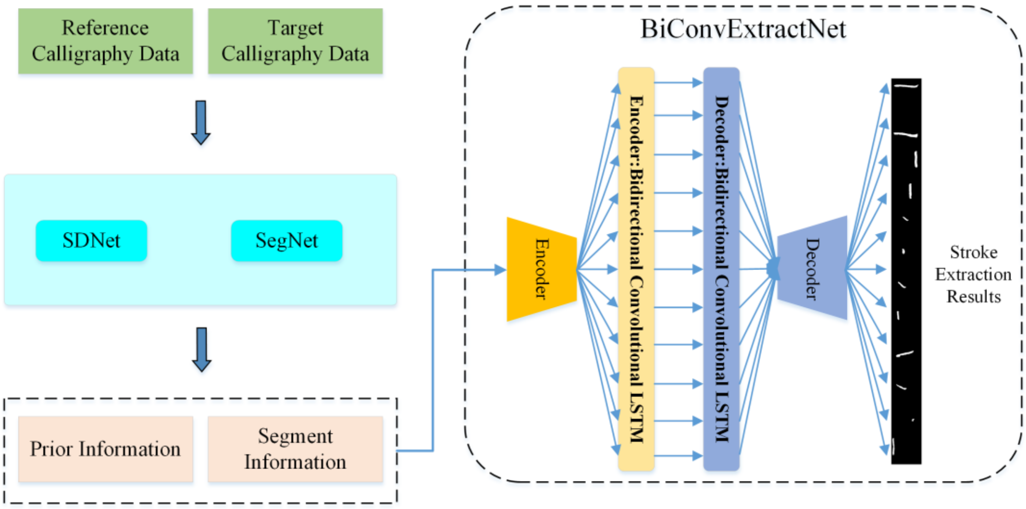

Figure 2: The structure of our stroke extraction method. The structure of the BiConvExtractNet is on the right side of the figure.

3.1.2. Loss and Train

In actual training, we take the weighted sum of the binary classification loss of all strokes as the final loss of the model. To improve the generalization of the model, we add a random position offset of 5 pixels to the reference calligraphy data and target data, and randomly adjust the stroke order. In order to obtain accurate overall features, we cancel the adaptive size scaling step in Li[12] method, which is used to increase the extraction weight of small-size strokes. Instead, we weight the stroke extraction loss using the inverse of the stroke area to increase the learning weight of small strokes. Experiments show that this method is effective.

3.2. Evaluation of Calligraphy Characters

The key to calligraphy assessment is to construct a complete effective evaluation strategy. Through the stroke extraction module, we achieve fine-grained decomposition of the target calligraphy data (decompose the entire character into single-strokes which are the smallest unit of writing). The strokes of the reference characters used in our method can be easily obtained in advance. We calculate the writing differences between the target calligraphy image and the reference image at the stroke level, radical level, and whole character level respectively, and summarize them into the final evaluation results. Combined with actual calligraphy evaluation experience, each evaluation part may contain multiple evaluation rules to calculate the difference between the target calligraphy image and the reference calligraphy image.

3.2.1. Whole Evaluation

Position difference: The positional deviation between the center of the target calligraphy image and the center of the reference calligraphy image.

Inclination difference: The deviation between the whole inclination angle of the target calligraphy and the whole inclination angle of the reference calligraphy image. The whole inclination angle is defined as the average of all single-stroke inclinations.

Size difference: The deviation between the target calligraphy size and the reference calligraphy size.

Shape difference: The ratio of the target calligraphy shape and the reference calligraphy shape.

Shape is defined as the aspect ratio of the calligraphy area.

3.2.2. Radical Evaluation

Distance difference: Deviation of the distance between the radical area center and the center of the whole calligraphy area.

Tightness difference: Deviation of the ratio of the average distance from the strokes within the radical to the center of the radical divided by the size of the radical.

3.2.3. Single-Stroke Evaluation

Length difference: The ratio of the stroke length of the target calligraphy stroke and the stroke length of the corresponding reference calligraphy stroke.

Thickness difference: The ratio of the stroke thickness of the target calligraphy stroke and the stroke of the corresponding reference calligraphy stroke.

Inclination difference: The deviation between the stroke inclination of the target calligraphy stroke and the inclination of the corresponding reference calligraphy stroke.

Curvature difference: The deviation between the stroke curvature of the target character and the curvature of the corresponding reference character. Circle approximation fitting is performed on the stroke skeleton. Curvature is defined as the arc occupied by the stroke skeleton.

3.2.4. The Final Evaluation Result

In order to unify the measurement range of the evaluation, we design a benchmark point for each evaluation point. Evaluation result is normalized to the range of (0,1), where 0 indicates the largest difference and 1 indicates consistency with reference calligraphy character. The final evaluation result is the average of all evaluation point results.

4. Experiments

4.1. Dataset

In the stroke extraction part, we use the calligraphy dataset CCSEDB in Li[12]. CCSEDB has a total of 5000 data, consisting of calligraphy characters, printed calligraphy characters, and calligraphy characters. Each piece of data in CCSEDB contains a target calligraphy image, corresponding reference calligraphy stroke image information, and annotated target single-strokes information.

In the calligraphy character evaluation part, we use images of students writing calligraphy characters as verification data. These data are directly collected from real calligraphy teaching scenes. The corresponding reference calligraphy information is constructed according to the CCSEDB format to facilitate stroke extraction.

4.2. Implementation Detail

In the experiments, for CCSEDB, we use 90% of the data for training and 10% for testing. The images of training data of our method have a resolution of 256. BiConvLSTM is trained with a batch size of 16 and an epoch of 100. The learning rate is initialized to 0.0001 and decreases by a factor of 0.5 every 30 epochs.

4.3. Stroke Extraction Results

We compare our method with recent best deep learning-based stroke extraction methods[12] named Path-MatchNet[13], PathNet[16], and ExtractNet[12] respectively. In order to quantify the stroke extraction results, we use the quantization method in [12]to calculate the quantization results under match and un-match with the reference stroke respectively. These two evaluation strategies are represented by *mIOUm* and *mIOUum* in [12].

Table 1: mIOUm and mIOUum of our method and baseline methods.

	Our Method	ExtractNet	PathNet	Path-MatchNet
mIOUm	**0.93**	0.921	\	0.687
mIOUum	**0.934**	0.925	0.84	0.843

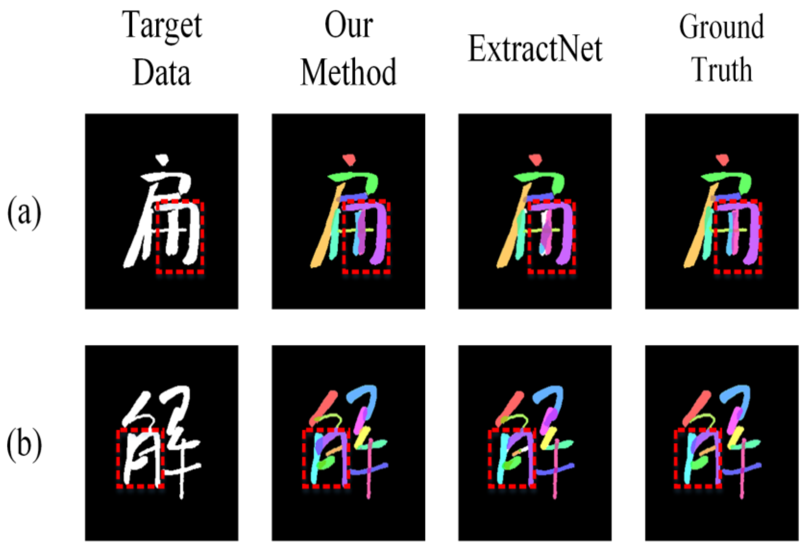

Figure 3: Comparison of stroke extraction results of our method and ExtractNet[12].

As shown in Table 1, in the stroke extraction part, adding analysis of the overall features can effectively improve the accuracy of stroke extraction. As shown in Figure 3, in some calligraphy characters with complex structures, especially when the strokes overlap each other, extraction errors are often easy to make. This is because the traditional method lacks overall analysis and there is no direct relationship between each stroke. Our method integrates individual stroke extraction into a single model through bidirectional convolutional LSTM. When obtaining a single stroke, you can refer to the already obtained strokes, which will reduce misjudgments in stroke extraction.

4.4. Calligraphy Evaluation Results

Table 2 shows some of our evaluation results. Our evaluation method gives evaluation results from three levels: whole character, radicals and single-strokes. The evaluation results obtained by our method can well reflect the quality of calligraphy handwriting. As shown in "Guo" in Table 2, the fourth stroke (storke_3 in Single-stroke Evaluation) of the target character is relatively long, so it gets a score of 0.42 in terms of length. In "Shan", the target calligraphy image is tilted to the right, so it gets a low score of 0.2 for the whole inclination (Whole Evaluation). Experiments show that the evaluation strategy summarized based on actual calligraphy teaching experience makes each of our evaluation results well interpretable. In addition, due to the use of fine-grained stroke-based evaluation mode, we can easily locate error strokes based on the evaluation results.

Table 2: Calligraphy evaluation results of our method. Whole evaluation contains four values (Position difference, Inclination difference, Size difference, Shape difference). Each radical in radical evaluation contains two values (Position difference, Tightness difference). Each stroke in single-stroke evaluation contains four values (Length difference, Thickness difference, Inclination difference, Curvature difference)

Character Name	Input Calligraphy Image	Whole Evaluation	Radical Evaluation	Single-stroke Evaluation	Final Evaluation Result
“Guo”	Target  Reference 	[0.9, 0.87, 0.79, 0.83]	[0.71,0.97]	stroke_0: [0.84, 0.85,0.57, 0.98] stroke_1: [0.99, 0.78, 0.75, 0.96] stroke_2: [0.89, 0.69, 0.67, 0.91] stroke_3: [**0.42**, 0.52, 0.89, 1.] stroke_4: [0.73, 0.85, 0.55, 0.97] stroke_5: [0.87, 0.56, 0.89, 0.88] stroke_6: [0.62, 0.83, 0.51, 0.83] stroke_7: [0.86, 0.89, 0.72, 0.94] stroke_8: [0.96, 0.8, 0.92, 0.82] stroke_9: [0.95, 0.95, 0.66, 0.98] stroke_10: [0.94, 1., 0.58, 1.] stroke_11: [0.98, 0.87, 0.66, 0.85]	0.80
“Shan”	Target  Reference 	[0.59, **0.2**, 0.98, 0.92]	\	stroke_0: [0.93, 0.79, 0.59, 1.] stroke_1: [0.53, 0.83, 0.79, 0.41] stroke_2: [1., 0.89, 0.7, 0.85] stroke_3: [0.95, 0.9, 0.4, 0.97]	0.73

5. Conclusions

In this paper, we propose an effective calligraphy character evaluation method based on deep stroke extraction. In our method, we first use the deep stroke extraction method to decompose the target calligraphy characters into single strokes. Then the calligraphy character evaluation method is used to obtain comprehensive evaluation results from multiple perspectives of the whole, radicals, and single strokes. Furthermore, considering the lack of overall analysis of the stroke extraction method, an optimization solution BiConvExtractNet based on bidirectional convolution LSTM is proposed. It effectively reduces the extraction errors caused by stroke intersection during the stroke extraction process. Experiments show that our calligraphy character evaluation method can achieve detailed and comprehensive evaluation results. Due to the fine-grained evaluation mode, error strokes and radicals can be easily located. In addition, BiConvExtractNet also performs better than previous stroke extraction methods.

We believe that evaluation strategy is the key to calligraphy evaluation methods. An effective evaluation strategy needs to fully consider the actual calligraphy teaching scenario. In the future, we will pay more attention to calligraphy character evaluation strategies and consider using new evaluation methods such as graph convolution-based which is more suitable for unstructured strokes and radicals in calligraphy characters.

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