A Novel Approach for Stroke Extraction of Off-line Chinese handwritten characters based on Optimum paths

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Abstract

In recognition of Off-line handwritten characters and signatures, stroke extraction is often a crucial step. Given the large number of Chinese handwritten characters, pattern matching based on structural decomposition and analysis is useful and essential to Off-line Chinese recognition to reduce ambiguity. Two challenging problems for stroke extraction are: 1) how to extract primary strokes and 2) how to solve the segmentation ambiguities at intersection points. In this paper, we introduce a novel approach based on Optimum Paths(AOP) to solve this problem. Optimum Paths(AOP) are derived from the degree information and continuation property, we use them to tackle these two problems. Compared with other methods, the proposed approach has extracted strokes from Off-line Chinese handwritten characters with better performance.

1. Introduction

Chinese handwritten characters always face the ambiguity problem due to the large number of samples with high complexity[1][2]. There are mainly two approaches to extract strokes from Chinese handwritten characters. One of them is to extract directly from binary images[3], and another is to extract from the skeletons. The former utilizes much information about stroke width and curvature. Its time consumption is considerably high. Meanwhile, the latter retains the information of stroke length and direction, with a relatively low consumption time, which is applied mostly in practical systems.

There are many methods of extracting strokes from a skeleton. Most stroke extraction methods use a thinning process, fast serial and parallel algorithms for thinning character images[4]. Most of them focus on the feature points such as fork points, connective points and end points[5][6] . Y.Y.Tang proposed a wavelet-based scheme to extract skeleton of Ribbon-like shape[7]. It is hard to guarantee the robustness for these approaches because of the variability of the handwritten Chinese characters. This paper proposes a stroke extraction model based on skeleton. The experiments indicate that this approach quite suitable for extracting strokes from handwritten Chinese characters.

The remainder of the paper is organized as follows: In section 2, we address how to extract the

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skeleton of a character. In section 3, we introduce our approach based on optimum paths. In section 4, we explain how to extract primary strokes and how to extract complete strokes. In section 5, we present some experimental results and discussions. Section 6 gives the conclusion.

2. Preprocessing

How to extract skeletons plays an important role in the preprocess of stroke extraction, generally, the skeleton of a shape is referred as the locus of the symmetric points or symmetric axes of the local symmetries of the shape. In other words, different local symmetry analyses may result in different symmetric points and, hence, different skeletons are produced. There are four methods for the local symmetry analysis, which are well-known to the shape analysis community, namely:

- Blum's Symmetric Axis Transform (SAT) [8],
- Brady's Smoothed Local Symmetry (SLS) [9], and
- Leyton's Process-Inferring Symmetry Analysis(PISA)[10].
- Tang's maximum moduli analysis of the wavelet transform (MMAWT)[7]

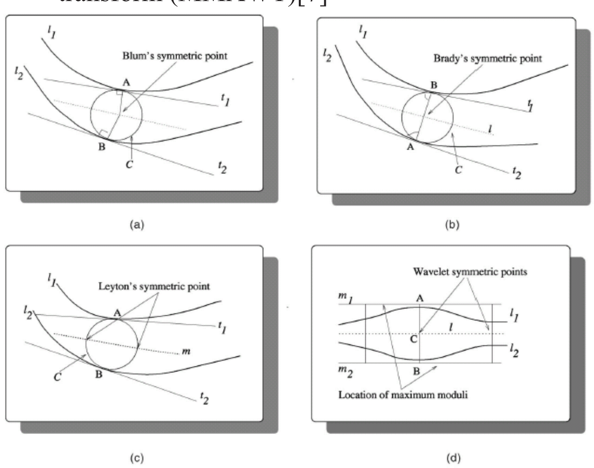

Figure 1. The illustration of symmetry analyses. (a) SAT. (b) SLS. (c) PISA.and (d) MMAWT.

The graphical descriptions of four symmetry analyses are shown in Fig. 1. Here, l_1 and l_2 are two opposite boundaries of the shape. A circle labeled by C is placed between l_1 and l_2 such that it is simultaneously tangential to both boundaries at points A and B in Figs. 1a, 1b, and 1c. Blum's symmetric axis transform (SAT) is shown in Fig. 1a, In SLS symmetry analysis, Brady defines the symmetric point of the local symmetry by the intersecting point of two symmetric lines of the symmetric circles as shown in Fig. 1b. Leyton's symmetric point is defined as the intersecting point of "mirror" m and symmetric circle C, the corresponding skeleton is defined by the locus of the midpoints of the symmetric arcs of the circles which can be shown in Fig. 1c. For MMAWT symmetry analysis, which is shown in Fig. 1d, the corresponding skeleton of a shape is defined as the locus of the midpoints of the segments connecting any pair of points, which lie on two opposite symmetric maximum moduli m_1 and m_2. The advantage is that a symmetric axis must be inside the shape entirely.

3. The stroke extraction approach based on Optimum Paths

We define the primary stroke in terms of the degree. The degree of a pixel is the number of branches incident on it. According to the degree information, a line image can be divided into three regions: end point regions, regular regions and singular regions. A pixel belongs to an end point region if its degree is equal to 1. If the degree of a pixel is equal to 2, it belongs to a regular region. Singular regions consist of pixels whose degree is 3 or greater than 3. (See Fig.2(a)) The primary stroke is the connected end point regions and regular regions.

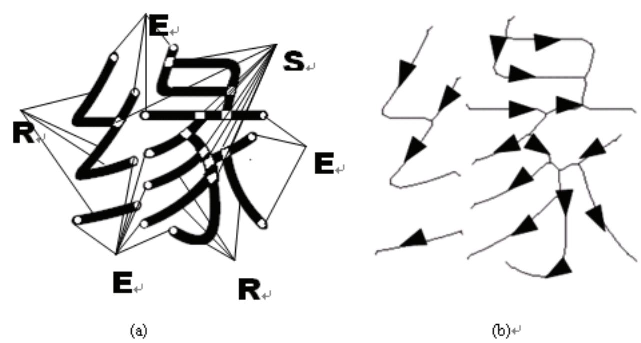

Figure 2. (a) Decomposition of a line picture into regular regions (R), end point regions (E), and a singular region (S), (b) character image unravels with direction[12].

We denote the contour curve of the character stroke using parametric equation $f(t) = (X(t), Y(t))$, where *t* is the arc length. The orientation of the curve is defined as[11] [11]

$$\alpha(t) = \tan^{-1}\left(\frac{dY/dt}{dX/dt}\right) \qquad (1)$$

where dY/dt and dX/dt stand for the derivatives along t of X and Y, respectively. To improve the orientation resolution, the orientation at the point P_i

can be defined by simply replacing the above derivative by the first difference.

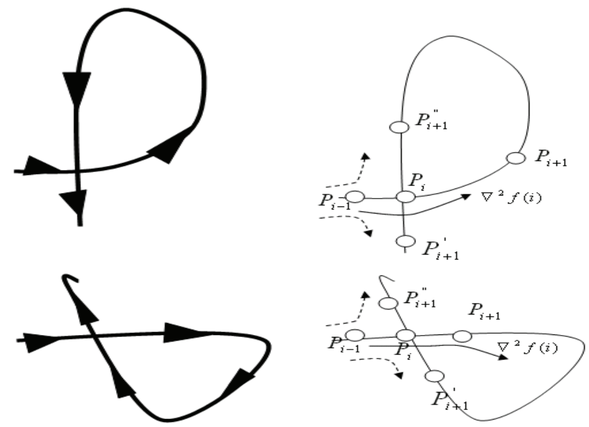

Figure 3. (a)A stroke move direction (b)When move passes the forkpoint of singular region , lookup next point uses algorithm of Optimum Paths(OP),the solid arrow shows correct direction and the dotted arrow represents error .

Hence, the direction at the point P_i is defined as

$$\alpha(i) = \tan^{-1}((Y_{i+1} - Y_{i-1})/(X_{i+1} - X_{i-1})) \qquad (2)$$

if point P_i in fig.2(b) singular region, the orientation of curve has more than one probability, point P_{i+1} will be in a different place, so our objective is to obtain the correct direction. Our search approach computes a search direction α_k and then decides how far to move along that direction. The P_{i+1} is given by

$$P_{i+1} = P_i + s_i \alpha_i \qquad (3)$$

where the positive scalar s_i is called the step length, suppose $s_i = 1$, our algorithms require α_i to be a descent direction because this property guarantees that the stroke function $f(i)$ moves along its direction. Moreover , the search direction often has the form

$$\alpha_i = -B_i^{-1} \nabla f(i) \qquad (4)$$

where B_i is the exact Hessian $\nabla^2 f(i)$ and a symmetric and non-singular matrix. To compute the direction, we seek a solution of the problem P''_{i+1}

$$\min_{\alpha \in R^2} m_k(\alpha) = f(i) + \nabla f(i)^T \alpha(i) + \tfrac{1}{2}\alpha(i)^T B_k \alpha(i) \quad (5)$$

Suppose P^* is a solution point along the correct direction, so

$$\begin{aligned} & P_i + \alpha(i) - P^* \\ &= P_i - P^* - \nabla^2 f(i)^{-1} \nabla f(i) \\ &= \nabla^2 f(i)^{-1} (\nabla^2 f(i)(P_{i+1} - P^*) - (\nabla f(i) - \nabla f^*)) \end{aligned} \qquad (6)$$

since $\nabla f(i) - \nabla f^* = \int_0^1 \nabla^2 f(P_i + t(P^* - P_k))(P_k - P^*)dt,$ we have

$$\begin{aligned} & \left\| \nabla^2 f(i)(P_{i+1} - P^*) - (\nabla f(i) - \nabla f^*) \right\| \\ &= \left\| \int_0^1 [\nabla^2 f(i) - \nabla^2 f(P_i + t(P^* - P_i))](P_i - P^*)\,dt \right\| \qquad (7) \\ &\le \left\| \int_0^1 \nabla^2 f(i) - \nabla^2 f(P_i + t(P^* - P_i)) \right\| \left\| P_i - P^* \right\| dt \\ &\le \left\| P_i - P^* \right\|^2 \int_0^1 Lt dt = \frac{1}{2} L \left\| P_i - P^* \right\|^2 \end{aligned}$$

where L is the Lipschitz constant for $\nabla^2 f(i)$ for P near P^*. By using $\nabla f(i) + \nabla^2 f(i)\alpha(i) = 0$, we obtain

$$\begin{aligned} \left\| \nabla f(i+1) \right\| &= \left\| \nabla f(i+1) - \nabla f(i) - \nabla^2 f(i)\alpha(i) \right\| \\ &\le \int_0^1 \left\| \nabla^2 f(i + t\alpha(i)) - \nabla^2 f(i) \right\| \left\| \alpha(i) \right\| dt \qquad (8) \\ &\le \tfrac{1}{2} L \left\| \alpha(i) \right\|^2 \\ &\le 2L \left\| \nabla^2 f(P^*)^{-1} \right\|^2 \left\| \nabla f(i) \right\|^2, \end{aligned}$$

This proves that the norm of the direction gradient converges to zero quadratically.

4. Extracting strokes

Through the study of the characteristic of skeleton and the existing models, we propose a stroke extraction model based on Optimum paths(AOP). The main idea of this model is to use computed paths to split a Chinese character into stroke segments and then select from them and merge them to correct strokes.

We summarize the proposed Optimum paths(AOP) model in the following.

Algorithm: Optimum paths(AOP)

1. Preprocessing stage: obtain digital image, compute skeleton of character X by the approach above. The output is the skeleton image of the handwritten character.

2. Find singular region and lookup for forkpoint F_i . We divide the circle into eight parts($2\pi/8$). Each part is a direction. We loop from the current point along the circle($k * 2\pi/8$) . If the next point exists, the $p_k = 1$, else $p_k = 0$ .When loop end,if $\sum_{i=1}^{8} p_k > 3$,so we make sure the point is a forkpoint .

3. Scan the skeleton image from right to left and from top to bottom . When meeting an end point $P_0 \neq 0$, we take it as a starting point of the stroke. So we lookup the next point based on the end

point P_0 , and we loop from the current point P_k along the direction circle($\theta = k * 2\pi / 8$) and use our Optimum Path method to find the next point P_{k+1} .

4. If we can't find the next point when loop is over, we take the point as end of stroke .

5. Group the point P_k which has been found and save it as a vector S_i ,label the point which has been checked.

6. Go back to step 3 until all points have been checked . Otherwise, the task can be terminated. Based on our algorithm , the vector S_i is the stroke which we want to extract from character X .

In this paper, we only address the stroke segmentation problem. As for obtaining dynamic writing information, after we get segmented strokes, we can utilize some popular human writing rules to determine the most probable writing direction of strokes. For example, Chinese characters usually follow the top-to-bottom and left-to-right rules.

In the character images, we get stroke segments in which some of them should be ignored, and we just concentrate on the legal ones. The legal stroke segment [13] is defined as that it has optimum curvature globally and locally, which lead to two algorithms.

Algorithm: Legal In Whole

1. Let the stroke segment be S and p_i (i=1,2,...,n) be the pixels in S.

2. Draw a line between the two end points of S, which is named as L .

3. Let the distance from p_i to L be d_i and the length of L be *len* .

4. Find out the max of d_i / len , which is named as M .

5. If M <0.16, return true, otherwise false.

Algorithm: Legal In Parts

1. Let the stroke segment be S .

2. Divide S into *i* equal parts, which are $p_j \, (j = 1,2,...,i)$ ...

3. If the pixel amount of $p_j < 15$, return true.

4. If all p_j is Legal In Whole, *j=j±1*, goto step2, otherwise return false.

After the selection of legal stroke segments from a character, we get too many legal stroke segments, and many of them are similar. Therefore, we take an algorithm called MergeSimilar[13] to merge the legal stroke segments into one, and an algorithm called MergeBroken[13] is used to merge some vertical or horizontal stroke segments together because of the complexity of the singular region.

5. Experiment

The proposed model was tested using a set of handwritten Chinese characters that are selected from a dataset. The number of characters in the testing set is 341. There are about 2049 strokes in total. The model segmented 1901 strokes correctly. The average accuracy is 92%. There are about 303 characters whose strokes are all segmented correctly. The average correct rate is 89%. Among the correctly segmented characters, the complexity is about 7 strokes per character on the average.

For each testing data, experiments were run on the follow algorithms:

1. With Brady's Smoothed Local Symmetry (AOP-SLS),
2. With Blum's Symmetric Axis Transform (AOP-SAT) ,
3. With Leyton's Process-Inferring Symmetry Analysis(AOP-PISA),and
4. With the wavelet transform (AOP-MMAWT),

The mean recognition accuracies across the different methods are summarized in TABLE I. (AOP-MMAWT) has a top accuracy 97.2%.Some of the typical cases are shown in Fig.4 to Fig.5. We can easily see that the proposed model performs better in preserving the connectivity of primary strokes (Fig.4) and separating overlapped strokes (Fig.5). The strokes extracted by the proposed model are closer to the correct way of segmenting a Chinese character. Images ahead of Fig.4 and Fig.5. show examples of handwritten characters. We can see that the proposed model can separate them successfully as long as the overlapped strokes are smooth at the intersections.

TABLE I. ACCURACY OF EXTRACTION STROKES WITH VARIOUS APPOACHES

	AOP-SLS	AOP-SAT	AOP-PISA	AOP-MMAWT
Character segment	84.5	87.3	88.5	90.7
Total accuracy	89.2	93.4	92.5	97.2

Figure 4. Strokes extracted from Chinese handwritten character "卷(juan)"

Figure 5. Strokes extracted from Chinese handwritten character "说(shuo)"

It is necessary to mention here that the strokes are not completely equivalent to the strokes defined as the path between pen-up and pen-down in the on-line character recognition system. This is one intrinsic difference between off-line and on-line system. Namely, on-line system traces pen-up and pen-down, whereas off-line system finds two ends of one line. When two strokes are linked end to end, they cannot be segmented from each other in the off-line case.

6. Conclusion

A new model of stroke extraction is proposed in this paper. First we extracted the primary skeleton using various methods. Then we proposed an AOP approach to solve the point movement at sigular regions.

The proposed model is performed entirely on thick-line character images, so no distortions are introduced. It also yields better performance in separating overlapped strokes and preserving connectivity of primary strokes. This model can be used to extract strokes from both printed and handwritten character images.

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