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Local Contour Features for Writer Identification

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Abstract. A method based on local contour features is proposed for writer identification in this paper. In preprocessing, an improved Bern-son algorithm is used to abstract contours form images. Then the distribution of local contour is extracted from the fragments which are parts of the contour in sliding windows. In order to reduce the impact of stroke weight, the fragments which do not directly connect the center point are ignored during feature abstraction. The edge point distributions of the fragments are counted and normalized into Local Contour Distribution Features (LCDF). At last, weighted Manhattan distance is used as similarity measurement. The experiments on our database show that the performances of the proposed method gets the state-of-art performance.

Keywords: writer identification, stroke feature, local contour distribution feature, weighted Manhattan distance.

1 Introduction

Writer identification is a hot area of computer vision and pattern recognition. According to the identification contents, writer identification methods fall into two major categories: text-dependent and text-independent [1]. In recent years, a variety of methods have been proposed for text-independent writer identification. These methods can be categorized into two kinds: model based and feature based. Model based methods build models and train the parameters from training images. Schlapbache et al.[2] builded a handwriting model by hidden Markov model and identified a writing image by its agreement with the model. He et al. [3] used hidden Markov tree model in wavelet domain to build the model of handwriting. Feature based methods focus on abstracting distinguish features for writer identification. Bulacu et al. [4] proposed a serial features with direction, angle for writer identification. Li et al. proposed a micro-structure feature [5], and improved it [6]. The micro-structure feature makes good performances on Chinese character identification. Ghiasi et al. [7] coded the local structures into a leng-angle form and used them to describe the direction of handwriting.

Learning from the idea of local structure distribution and extending it to general case, a method base on Local Contour Distribution Feature (LCDF) is

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proposed in this paper. LCDF reflects the writing style by counting the distribution of stroke in sliding windows. In order to reduce the impacts of stroke weights and irrelevant structures, only the edge points directly connecting the center point are counted in the sliding window. At last, the weighted Manhattan distance is used to measure the similarity between two LCDFs. The experiments on our database show that the proposed method gets state-of-art performance of the methods.

2 Feature abstraction and similarity measurement

The proposed method contains two main parts: feature abstraction and similarity measurement. For our feature is extracted from the stroke contour, an contour detection preprocessing is required.

2.1 Contour detection preprocessing

Bernsen algorithm [8] is a local binarization method and better for uneven illuminative images. This algorithm should be operated in sliding windows. In a sliding window, the center point is (x, y), the max value is $\max f$ and the min value is $\min f$, where f contains values of all pixels. The definition of Bernsen algorithm in sliding window is

$$T(x,y) = \frac{\max f + \min f}{2}. \tag{1}$$

Then, the binarization result can be obtained by

$$B(x, y) = \begin{cases} 0 & \text{if } f(x, y) < T(x, y) \\ 255 & \text{else} \end{cases}. \tag{2}$$

The shortcoming of Bersen algorithm is over-segmentation in uniform regions. So it is not a reasonable binarization method by equation (2) when the difference between the max and min is too small. Considering even regions are not inner regions of strokes in most conditions, the binarization method is modified to

$$B(x, y) = \begin{cases} 0 & \text{if } f(x, y) < T(x, y) \text{ and } T(x, y) > T \\ 255 & \text{otherwise} \end{cases}. \tag{3}$$

where T is a threshold.

2.2 Fragment extraction

The rectangle in Fig. 1 is a sliding window. Its center is an edge point marked with ”+”. The size of the window is $(2r + 1) \times (2r + 1)$, where $2r + 1$ is the length of a side of the window. There are several fragments in the window, which are parts of the contour. In the conditions of any writing instruments allowed, handwritings with different weight will be obtained from a same writer. So the stroke weight has a negative influence in writer identification. In order to reduce the influence of stroke weight, the fragments not connecting the center point are ignored. Fig. 1 shows the local fragment extraction process. There are two fragments in the window and only the one connecting center point is used in next step.

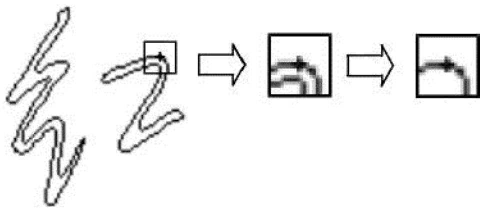

Fig. 1. The fragment extraction in a sliding window.

2.3 The LCDF extraction

The stroke distribution can reveal hidden features of stroke. The probability distribution of local structure in sliding windows is used in literature [5,6]. The sliding window goes through the image with all edge points as its center.

The feature counting window in literature [5, 6] is showed in Fig. 2. Its center is an edge point marked with black. The gray sites are edge points of the fragment connecting the center. The subscript of every site is its group number. For a 7×7 window, there are three groups. In literature [5,6], the numbers of some related site pair are counted, such as the same group pairs (123, 203), (82, 132) and (41, 71), the adjacent group pairs (41, 82), (71, 132), (82, 123) and (132, 203), the interval group pairs (41, 123) and (71, 203). These related group pairs can depict the local structure distribution.

The existing local features only used a subset of related site pairs. A reasonable extension of these ideas is considering more pairs may gain a more powerful feature. The proposed feature uses the pairs whose first group number is no less than the second number. Then, the feature is abstracted by next steps:

(1) Contour detection. It is an important preprocessing. Sobel detector is useful for simple background images, while an improved Bernsen algorithm is valuable for complex background images.

(2) Local fragment extraction. The method is shown in section 2.2.

(3) Counting the number of (I*m*1, J*m*2), where I and J are two related points in a sliding window, m1 and m2 are their group numbers, m1 m2.

(4) Go through all edge points and repeat step (2) and (3).

(5) Normalization. Different images have different numbers of edge points. So, the distribution should be normalized. In our experiments, it is normalized with

9_3	8_3	7_3	6_3	5_3	4_3	3_3
10_3	6_2	5_2	4_2	3_2	2_2	2_3
11_3	7_2	3_1	2_1	1_1	1_2	1_3
12_3	8_2	4_1		0_1	0_2	0_3
13_3	9_2	5_1	6_1	7_1	14_2	23_3
14_3	10_2	11_2	12_2	12_2	13_2	22_3
15_3	16_3	17_3	18_3	19_3	20_3	21_3

Fig. 2. Feature counting window in literature [5, 6].

$\sum_{I_m} N(I_m)$, where $N(I_m)$ is the number of edge points. Then, the probability density of coding becomes

$$p(I_{m1},J_{m2}) = \frac{N(I_{m1}, J_{m2})}{\sum_{I_m} N(I_m)}, \tag{4}$$

where $N(I_{m1}, J_{m2})$ is the number of pair (I_{m1}, J_{m2}).

The main part of feature extraction is repeat counting, which is an easy way of realization. As the size of sliding window increases, the feature dimension rapidly increases and most features far from center tends to be nearly useless for their close to zero values. So, the size of sliding window is limited in a small range. In our experiments, three kinds of window sizes are used: 11 x 11, 13 x 13 and 15 x 15.

2.4 Similarity measurement

The methods of similarity measurement fall into two major categories: model based and distance based. Considering the model is more time consuming and difficult to describe the relations between stroke and its surroundings, the proposed method directly computes the distance between two features and measures the similarity by the nearest neighbor rule.

Several distance measurements and their weighted measurements have been tested in our experiments. Among these methods, the weighted Manhattan distance has obtained the best performance, whose definition is

$$D_i = \frac{|LCDF_{1i} - LCDF_{2i}|}{\sigma_i}, \tag{5}$$

where σ_i is standard deviation of the ith component of LCDFs, $LCDF_{1i}$ and $LCDF_{2i}$ are the ith components of two LCDFs, respectively.

3 Experiments

To evaluate the effectiveness of the proposed method, we test it on our writer database. Distances between any two document images of the database are calculated by the weighted Manhattan distance. These results are sorted from the most similar to the less similar image. Then, two different measurements soft TOP-N and hard TOP-N criterion are used to evaluate the performance of the proposed method. Soft TOP-N criterion is the accuracy of at least one of the same writer is included in the N most similar document images. While hard TOP-N criterion is the accuracy of all the N most similar document images are written by the same writer. Hard criterion is more strict.

Handwritings of our database are from fifteen writers. Each writer has three document images and each image has about fifty Chinese characters. These images have inhomogeneous intensities and obvious noise because of the low performance of our scanner. So they are binarized by the improved Bernsen algorithm. The values of N used for the soft criterion are 1, 2, 5 and 10. For every writer only has three images, the value of N used for the hard criterion is 2.

The proposed method is a local structure method. The method of [6] has relative high performance among the existing methods. So we realized this method for comparison. Table 1,2 show the performance on our database. The high performance of our method show LCDF is more powerful than the existing local structure features.

Table 1. Performance on our database (soft evaluation).

method	sliding window size	Top-1	Top-2	Top-5	Top-10
Method of [6]	11 x 11	96.5%	96.5%	100%	100%
	13 x 13	96.5%	97.8%	97.8%	100%
	15 x 15	93.3%	97.8%	97.8%	100%
The proposed method	11 x 11	97.8%	97.8%	100%	100%
	13 x 13	97.8%	100%	100%	100%
	15 x 15	97.8%	97.8%	100%	100%

Table 2. Performance on our database (hard evaluation).

method	sliding window size	Top-2
		11 x 11
Method of [6]		7
		3.3%
		11 x 11
The proposed method		8
		0.0%

4 Conclusion

In this paper, a method based on LCDF is proposed. The contour is detected by an improved Bernsen algorithm. Then LCDF is extracted from the sliding windows by counting the edge point distribution of the fragments. In order to reduce the impact of the stroke weight, only the fragments connecting the centers of sliding windows are counted. Our feature is more powerful than the existing local structure features by counting more related pairs. At last, the weighted Manhattan distance effectively measures the similarities of the LCDFs. The experiments on our database show the good performance of our method.

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