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Writer Identification Based on Local Contour Distribution Feature

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Abstract

A method based on local contour distribution features is proposed for writer identification in this paper. In preprocessing, contours are abstracted form images by an improved Bernson algorithm. Then the Local Contour Distribution Feature (LCDF) 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 in the feature abstraction procedure. The edge point distributions of the fragments are counted and normalized into LCDFs. At last, the weighted Manhattan distance is used as similarity measurement. The experiments on our database and ICDAR 2011 writer identification database show that the performance of the proposed method reach or exceed those of existing state-of-art methods.

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

1. Introduction

Because the handwriting of a person is unique, it can be used for writer identification. With writer identification being widely used in various fields, computer technology based automatic writer identification has become a hot research area in computer vision and pattern recognition.

Writer identification methods fall into two major categories: text-dependent and text-independent [1]. Text-dependent methods require writers to write the same fixed text with the training handwritings. Signature verification [2, 3], which is widely used in credit cards, is one of text-dependent writer identification. In text-independent methods, any handwriting documents with different text will be useful. As any text with different characters is used to extract writing styles, their feature extractions are more difficult. In most conditions, it is impossible to have same texts in different documents. So the text-independent methods have wider applications.

In addition, according to the different ways of obtaining handwritings, writer identification can be divided into on-line and off-line [4]. The information of writing order and dynamics is available in on-line way. While in an off-line way, only scanned images are available and much dynamic information is lost.

In recent years, a variety of methods have been proposed for off-line and 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. Their identification can be seen as a procedure of calculating the similarities between

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the model and handwriting documents. Schlapbache *et al.*, [5] built a handwriting model by hidden Markov model and identified a handwriting by its agreement with the model. He *et al.*, [6] used hidden Markov tree model in wavelet domain to build the model of handwritings. Feature based methods focus on abstracting distinguish features for writer identification. Bulacu *et al.*, [7] proposed a serial features with direction, angle for writer identification. Li et al. proposed a micro-structure feature [8], and later improved it [9]. Their micro-structure feature makes good performance on Chinese character identification. Ghiasi *et al.*, [10] coded the local structures into a length-angle form and used them to describe the direction of handwriting. Fiel *et al.*, [11] used the SIFT features to avoid the negative effects of binarization. Wen et al. [12] found the features by counting the coding.

Learning from the idea of local structure distribution and extending it to general case, a method base on Local Contour Distribution Feature (LCDF) is proposed in this paper. LCDF shows the writing style by counting the distribution of stroke in sliding windows. In order to reduce the impacts of stroke weights and irrelevant structures, the abstraction procedure only counts the edge points directly connecting the center point in the sliding window. At last, the weighted Manhattan distance is used to measure the similarity between two LCDFs. The experiments on our database and ICDAR 2011 writer identification database [13] show that the proposed method reaches or exceeds the performance of the state-of-art methods.

2. Feature Abstraction and Similarity Measurement

The proposed method contains two main parts: feature abstraction and similarity measurement. Our feature is extracted from the stroke contour. So, an edge detection preprocessing is required. The feature abstraction procedure counts the edge points in sliding windows and normalized the distribution into LCDF. Then, the similarity is identified by the distance calculated by the weighted Manhattan distance.

2.1. Contour Detection Preprocessing

Edges contain many stroke features such as directions, length and angles. These features have been successfully used for writer identification in previous literature. Edge of uniform background images can be detected by simple methods such as Sobel detector. But for complex images, more complex methods should be used.

Bernsen algorithm [14] 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 represents all of the pixel values. The definition of Bernsen algorithm in sliding window is

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

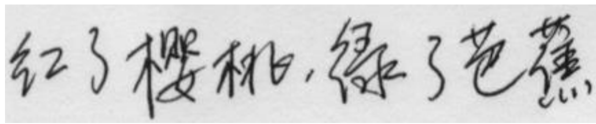
Then, the binarization result can be obtained by

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

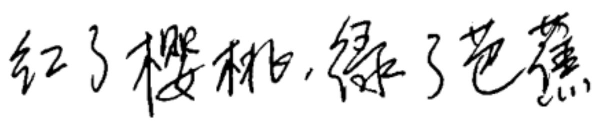
The shortcoming of Bersen algorithm is over-segmentation in uniform brightness regions. So it is not reasonable to get a threshold image by equation (2) when the difference between the max and min is too small. Considering even regions are not inner parts of strokes, the binary method is modified to

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

where T is a threshold. Figure 1 shows an example of preprocessing: (a) is the original image, (b) is the binary result by equation (3) and (c) is the contour of (b).



(a)



(b)

(c)

Figure 1. Contour Detection Preprocessing. (a) is an Original Image, (b) is the Binarization of (a), and (c) is the Contour From (b)

2.2. Fragment Extraction

The rectangle in Figure 2 is a sliding window. Its center is an edge point marked with "+". The size of the window is $(2r+1)\times(2r+1)$, where r is the distance between the center and the border of the rectangle. In the window, there are several fragments which are parts of the contour. Only the fragment connecting the center is counted in literature [15]. In the conditions of any writing instruments allowed, a writer will give handwritings with different weights. So the stroke weight has a negative influence for writer identification. In order to reduce the influence of stroke weight, the fragments not connecting the center point are ignored. Figure 2 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.

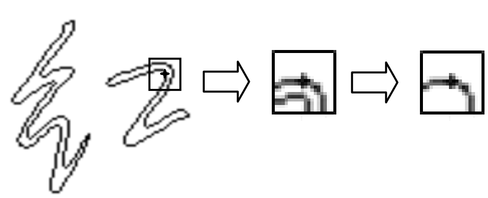


Figure 2. The Fragment Extraction in a Sliding Window

2.3. The LCDF Extraction

The stroke distribution can reveal the hidden feature of the strokes. The probability distribution of local structure in sliding windows is used in literature [8, 9, 12, 15]. The sliding window goes through the image with all edge points as its center.

The feature counting window in literature [8, 9] is showed in Figure 3. The center is an edge point marked with black color. 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 [8, 9], the numbers of some related site pair are counted, such as the same group pairs $(12_3, 20_3)$, $(8_2, 13_2)$ and $(4_1, 7_1)$, the adjacent group pairs $(4_1, 8_2)$, $(7_1, 13_2)$, $(8_2, 12_3)$ and $(13_2, 20_3)$, the interval group pairs $(4_1, 12_3)$ and $(7_1, 20_3)$. They used these related group pairs to depict the local structure distribution. Though the related pairs are coded in literature [12], the fundamental is the same with [8, 9].

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

Figure 3. Feature Counting Window in Literature [8, 9]

A local fragment feature called edge co-occurrence matrix (ECM) is used to distinguish handwriting and machine printed text in literature [15]. ECM only counts the relation between center and other points. The low dimension of this feature makes it have low performance in writer identification.

The existing local features only used a subset of related site pairs. A reasonable extension of these ideas is considering more pairs to gain a more powerful feature. A pair sites have two group numbers. If the first group number is no less than the second, more pairs are considered when the sites near the center and less pairs are considered otherwise. There are two reasons for using these pairs. The first reason is that a little deviation of the sites near center will cause a negative influence of results for their high probability values. The second is considering all pairs will cause a lot of repeating computation.

The flow chart of feature abstraction is shown in Figure 4.

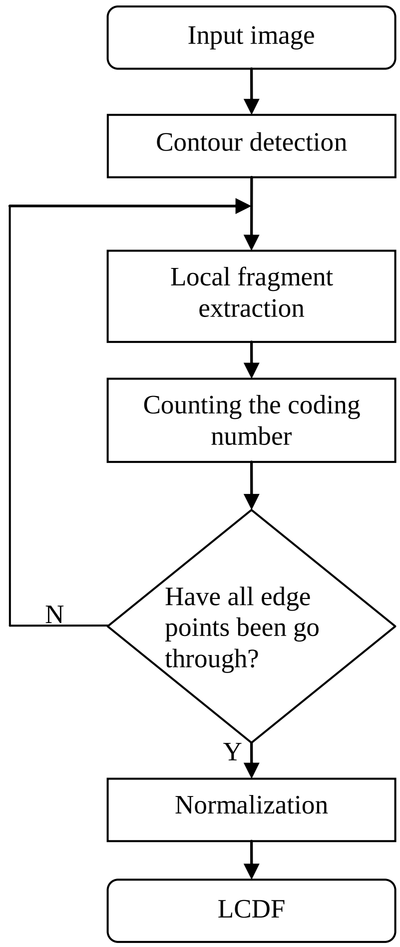


Figure 4. The Flowchart of LCDF Extraction

1) Contour detection. It is an important preprocessing. Sobel detector is useful for simple background images, and the 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_{m1}, J_{m2}), where I and J are two related sites in a sliding window, $m1$ and $m2$ are their group number, $m1 \leqslant m2$.

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

5) Normalization. The numbers of edge point are not same in different images. So, the distribution should be normalized. In our experiments, it is normalized with $\sum_{I_m} N(I_m)$, where $N(I_m)$ is the number of site I_m.

Then, the probability density of coding is

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

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

The obtained LCDF is shown in Figure 5. The size of example window is 7×7, every site contains the probability densities of the pairs between the current site and other sites.

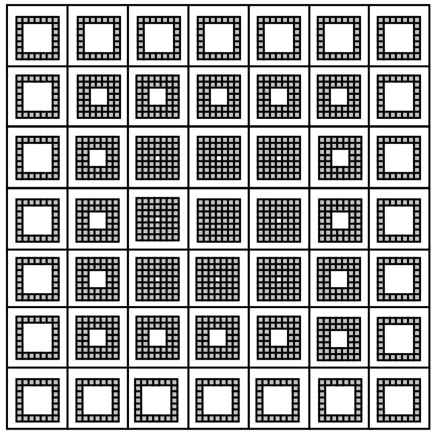


Figure 5. An example of LCDF

The main part of feature extraction is repeated counting, which is easy to realize. As the increasing of sliding window size, the feature dimension rapidly increases and most features far from center tend to be useless since their values are close to zero. So, the size of sliding window is limited in a small range. In our experiments, three kinds of windows are used: 11×11, 13×13 and 15×15.

2.4. Similarity Measurement

The methods of similarity measurement fall into two major categories: model based and distance based. Model based methods train models by a series labeled data and measure the similarity by how well the data fits the model. Considering that 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

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

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

3. Experiments

The proposed method has been applied on our writer database and ICDAR 2011 writer identification database.

Two different measurements soft TOP-N and hard TOP-N criterion are used to evaluate the performance of the proposed method. Every document image of the database is calculated its distances to all other document images using the weighted Manhattan distance. The results are sorted from the most similar to the least similar image. The 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 the hard TOP-N criterion is the accuracy of all the N most similar document images are written by the same writer. It is a more strict criterion and difficult to get a high accuracy.

Fifteen writers are included in our database. Each writer has three document images and each image has about fifty Chinese characters. Figure 6 shows an example of our database. The image is uneven illumination and has obvious noise because of the low performance of our scanner. So the images are binarized by the improved Bernsen algorithm. The values of N used for the soft criterion are 1, 2, 5 and 10. For each writer, there are only three images. So, the value of N is 2 in the hard criterion.

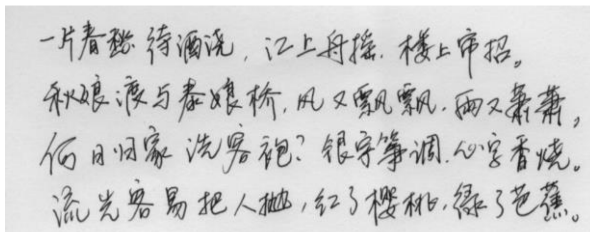


Figure 6. An Example of Our Database

The proposed method is a local structure method. The method of [9] has a relative high performance among the existing methods. So we realized the method for comparison. Tables 1 and 2 show the performance on our database. The high performance of our method shows that the LCDF is more powerful than the existing local structure features.

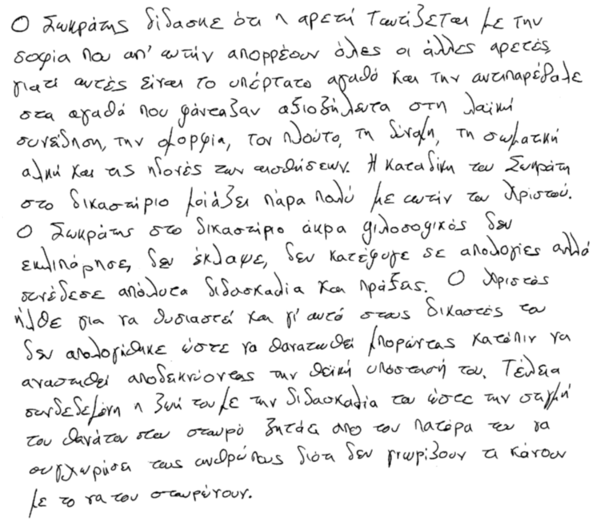
Table 1. Soft Evaluation using our Database

methods	*Window size*	*TOP-1*	*TOP-2*	*TOP-5*	*TOP-10*
Method of [9]	11×11	95.6%	95.6%	100%	100%
	13×13	95.6%	97.8%	97.8%	100%
	15×15	93.3%	97.8%	97.8%	100%
The proposed	11×11	97.8%	97.8%	100%	100%
	13×13	97.8%	100%	100%	100%
	15×15	95.6%	97.8%	100%	100%

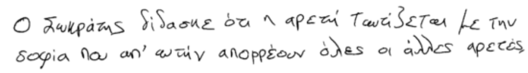
Table 2. Hard Evaluation using our Database

methods	*Window size*	*TOP-2*	*Window size*	*Window size*	*TOP-2*
Method of [9]	11×11	73.3%	The proposed	11×11	80.0%
	13×13	68.9%		13×13	71.1%
	15×15	66.7%		15×15	71.1%

To evaluate the effectiveness of the proposed method, we also test it on ICDAR 2011 writer identification database. ICDAR 2011 Writer Identification Contest is the first contest and its database is consisted with 26 writers who were asked to copy eight pages. They applied two different evaluation scenarios. In the first scenario, the original images of the dataset are used. In the second scenario, the images are cropped. Figure 7 shows two examples of these two scenarios. A cropped image has much fewer characters than an original image, which increases the difficulty of feature abstraction. The values of N used for the soft criterion are 1, 2, 5 and 10 and the values of N used for the hard criterion are 2, 5 and 7.



(a)



(b)

Figure 7. Examples of ICDAR2011 Writer Identification Database. (a) is an Example of Original Image and (b) is the Result of ECM

Tables 3-6 show the comparisons of the proposed method with other methods mentioned in ICDAR 2011. In Tables 3-6, the highest accuracy results are marked in bold. The size of sliding window used in these experiments is 13×13. Though the performance of the proposed method in original scenario is slightly below the highest, its performances in cropped scenario exceed the existing methods.

Table 3. Soft Evaluation using ICDAR Database of Original Images

Methods	*TOP-1*	*TOP-2*	*TOP-5*	*TOP-10*
ECNU	84.6%	86.5%	88.0%	88.9%
QUQA-a	90.9%	94.2%	98.1%	99.0%
QUQA-b	98.1%	98.6%	99.5%	**100.0%**
TSINGHUA	**99.5%**	99.5%	**100.0%**	**100.0%**
GWU	93.8%	96.2%	98.1%	99.0%
CS-UMD	**99.5%**	99.5%	99.5%	99.5%
TEBESSA	98.6%	**100.0%**	**100.0%**	**100.0%**
MCS-NUST	99.0%	99.5%	99.5%	99.5%
The proposed	98.6%	99.0%	99.0%	99.5%

Table 4. Hard Evaluation using ICDAR Database of Original Images

methods	*TOP-2*	*TOP-5*	*TOP-7*
ECNU	51.0%	2.9%	0.0%
QUQA-a	76.4%	42.3%	20.2%
QUQA-b	92.3%	77.4%	41.4%
TSINGHUA	95.2%	**84.1%**	41.4%
GWU	80.3%	44.2%	20.2%
CS-UMD	91.8%	77.9%	22.1%
TEBESSA	**97.1%**	81.3%	50.0%
MCS-NUST	93.3%	78.9%	38.9%
The proposed	94.2%	82.7%	**46.2%**

Table 5. Soft Evaluation using ICDAR Database of Cropped Images

methods	*TOP-1*	*TOP-2*	*TOP-5*	*TOP-10*
ECNU	65.9%	71.6%	81.7%	86.5%
QUQA-a	74.0%	81.7%	91.8%	96.2%
QUQA-b	67.3%	79.8%	91.8%	94.7%
TSINGHUA	90.9%	93.8%	**98.6%**	**99.5%**
GWU	74.0%	81.7%	91.4%	95.2%
CS-UMD	66.8%	75.5%	83.7%	89.9%
TEBESSA	87.5%	92.8%	97.6%	**99.5%**
MCS-NUST	82.2%	91.8%	96.6%	**99.5%**
The proposed	**96.2%**	**97.6%**	**98.6%**	98.6%

Table 6. Hard Evaluation using ICDAR Database of Cropped Images

method	*TOP-2*	*TOP-5*	*TOP-7*
ECNU	39.4%	2.9%	0.0%
QUQA-a	52.4%	15.9%	3.4%
QUQA-b	47.6%	22.6%	6.3%
TSINGHUA	79.8%	48.6%	12.5%
GWU	51.4%	20.2%	6.3%
CS-UMD	51.9%	22.1%	3.4%
TEBESSA	76.0%	34.1%	14.4%
MCS-NUST	71.6%	35.6%	11.1%
The proposed	**85.1%**	**51.4%**	**15.9%**

4. Conclusion

In this paper, a method based on LCDF is proposed. The contour is detected by an improved Bernsen algorithm and the fragments are the contour in sliding windows. 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. The counting procedure is easily to be implemented, which mainly consists of the repeated additions. Our feature is more powerful than the existing local structure features by counting more related pairs. Lastly, the weighted Manhattan distance effectively measures the similarities of the LCDFs. The experiments on our database and the ICDAR database show the performances of our method has reached or exceeded that of the state-of-art methods.

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