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Handwritten recognition based on depth learning and temporal logic

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Abstract. As a safe and reliable biological recognition technology, writer identification in the field of pattern recognition had received extensive attention. This paper proposes a method for writer identification based on LCDF feature. The edge points were divided into 32 direction categories, which obtained the balance between the performance and complexity. The effect of stroke thickness was reduced through removing the contour which is not directly connected to the center point in the sliding-window in the statistical process of features. The statistical process of features was a simple superposition of relevant feature encodings with simple algorithm and easy to realize. The weighted Manhattan distance effectively measured the similar degree between features. The proposed LCDF feature had counted the probability distribution of each position location feature in the local window, which can reflect the trend of stroke and local structure. The experiment shows that the proposed method achieves better identification accuracy on the multi-language test database in the ICDAR2011 writer identification competition, of which some indexes exceed the current advanced algorithm.

Key words. Writer identification, Depth learning, Feature classification, Machine learning, Stroke feature, Local contour direction feature.

1. Introduction

Writer identification is a biological recognition method to identify the text handwritings by the use of writing features of human, it can provide an important basis for authentication, and has a wide range of applications in the security fields. The handwriting identification can be divided into on-line and off-line two kinds of identification method according to the way of obtaining handwriting [1]. The weight and trends and other features of writing can be obtained in on-line mode, of which more information can be used, and obtained a higher accuracy in previous study. The collected handwritings are usually input in the computer and saved the form of image through scanning and other methods in off-line mode with a flexible access and has

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a wider range of applications. Off-line mode is to obtain the image information of handwritings, generally it is judged only through the structure of the handwriting and other features, so it has strong difficulty in identification, and recognition rate is lower than that of in the on-line mode.

In recent years, various off-line writer identification methods had been put forward in many Literatures and algorithm performance had been greatly improved. These algorithms can be roughly divided into two categories: model method and feature statistical method. In the model method, the handwriting is established as a model with parameters, and the existing handwriting trainings are used to determine the parameters, of which its identification process can be interpreted to calculating the matching degree between the handwriting and the existing models. Schlapbach et al. [2] put forward the Hidden Markov Model (HMM) to establish the model of handwriting line. He et al. [3] used the Hidden Markov Tree Model with wavelet domain for Chinese handwriting identification. Feature statistical method makes use of the similar structures with stable statistical distribution in a great deal of handwritings for handwriting identification. Bulacu et al. [4] put forward features of a series of stroke direction, included angle and local structure of strokes, of which its statistical features are used for handwriting identification. Li Xin et al. .[5] put forward a microstructural statistical feature for handwriting identification and improvements have been proposed based on this method. [6], which obtained a better performance in Chinese handwriting identification. Ghiasi et al. [7] encoded the local structure as the form of length and angle to describe the trend and trend features of handwriting. Fiel et al. [8] used statistical features of SIFT, which avoided the labile factors brought by binaryzation and other preprocessings. Wen et al. [9] encoded the local structure and found the implicit features of handwriting through analyzing the statistical features of the coded value.

2. Feature extraction and similarity measurement

Direction of strokes can mark the trend of handwriting to reflect the features implied in the image. In this paper, statistical features of LCDF were used for writer identification, and the whole method is mainly divided into two parts: feature extraction and similarity measurement. Original drawing of handwriting contains much useful information, and at the same time contains a great deal of redundant information. The edge of handwriting contains many features, of which can fully recover the original form of handwriting. The edge extraction algorithm is used in the process of preprocessing, because LCDF feature is obtained from the edge information of handwriting. A better edge extraction effect is achieved in the experiment by adopting Sobel operator due to the simple background of test image. Shown as Fig. 1, (a) is the effect of handwriting image, and (b) is the edge obtaining from (a). Feature extraction is a process of statistical eigenvector in edge image of handwriting. Similarity measurement is to calculate the distance between the eigenvectors, of which its similarity degree is represented by distance.

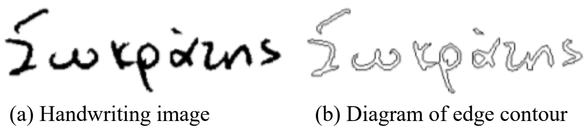


Fig. 1. Handwriting image and its edge contour

2.1. Extraction of local contour direction feature

Everyone's handwriting has its own inherent property, and handwriting can be naturally identified by using the beginning, heading and the last withdrawal method of handwriting. According to this basic principle and the idea of probability distribution, this paper proposes a feature based on the local contour direction, which is used to represent the change direction and trend of the edge. The process of obtaining the LCDF feature is shown as Fig. 2, including steps such as preprocessing of the edge extraction, cyclic statistical feature and normalization. The cyclic statistical feature is the main part of feature extraction, which needs two preparation processes: direction feature of edge points and obtaining of local contours.

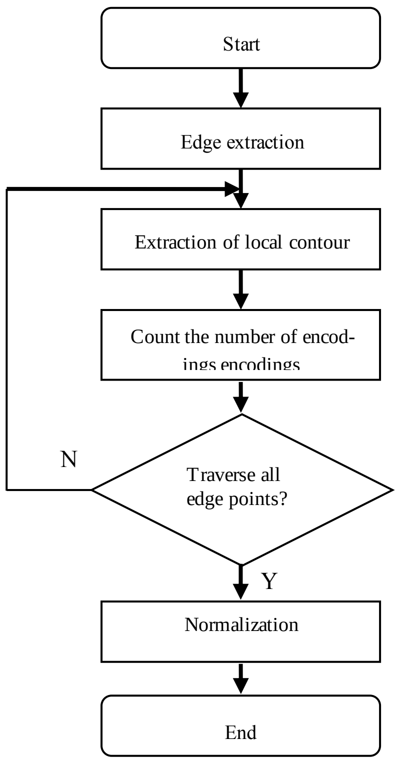


Fig. 2. Flow chart of LCDF feature extraction

(1) Edge point direction feature

In order to obtain the direction features of handwriting, it is necessary to define the direction of edge points, and count the number of each direction, and then obtain the intrinsic statistical features of handwriting structure. Through analyzing the relationships between the edge points and surrounding contours, direction distribution conditions of contour centered as the current edge point in 5×5 window are divided into 32 categories shown as Fig. 3. Dividing into 32 categories is the results of comprehensive performance and complexity. Performance in the experiment slightly decreases 5×5 only taking 8 directions in 3×3 window into consideration. The number of category will quickly increase when taking 7×7 window or even larger windows into consideration, which is not easy to realize. An edge point allows to having multiple directions, and other conditions that do not belong to 32 categories are ignored to simplify the algorithm.

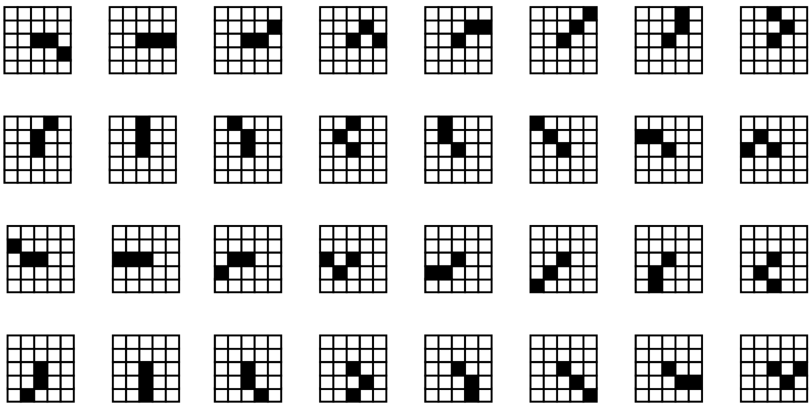


Fig. 3. 32 direction categories of edge point

(2) Local contour

Take an edge point as the center, and intercept a window on contour of writing as shown in Fig. 4 to obtain the information of the local stroke direction, length and so on. The center of the window is represented by "+", the size is, $(2r+1) \times (2r+1)$, of which is r the distance from the center point to the boundary. In order to remove the influence of irrelevant points as much as possible. The contour disconnected with the central pixel shall be neglected in the window, and only the edge pixels connected with the center are obtained. The acquisition process of the local contour is shown in Fig. 4. There are three-section edge contours in the window, and the proposed method only uses the section directly connected with the center.

To obtain the statistical features of contours is described in detail in Literature [11]. The use of this local contour can reduce the impact of stroke thickness. Stroke thickness plays both advantages and disadvantages role in writer identification. The advantage is that it can reflect the difference in the strength of each handwriting, and the disadvantage is that if the same person uses different pens, they will get different thickness of handwriting, that is to say, the stroke thickness is not suitable for the handwriting features. Therefore, in the absence of restrictions on the use of what kind of writing tools, impact of reducing the handwriting thickness as far as

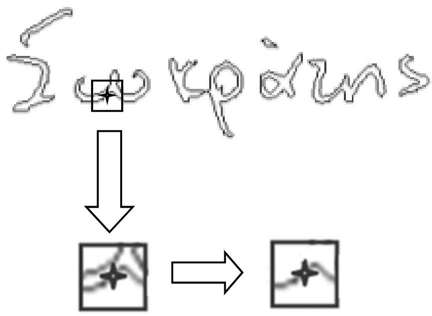


Fig. 4. Local contours in sliding-window. The contours disconnected with the central pixel are neglected, and only the edge fragments connected with center are retained.

possible is more benefit.

(3) Steps for LCDF feature extraction

The direction information of the handwriting can be obtained by directly counting the direction features of all the edge points. However, the reliability of identification is not satisfactory due to its small range. A feasible method is to calculate the direction features of all positions in a local window, and obtain a larger range of direction feature so as to improve the reliability of features. In combination with the preprocessing process, the process of the proposed LCDF feature extraction is:

1) Edge extraction. Edge extraction is an important preprocessing process. This paper only uses the Sobel operator. For the complicated background, Canny and other edge methods can be considered to use.

2) According to the method described in the Part 2 of this Section, the edge points in the sliding-window are taken as the local contours of the center.

3) Obtain the encodings (m, n, d_i) of all the edge points in the local contour, and counts the times of all the encoding appear. (m, n) is the coordinate of point in the sliding-window, $1 \leqslant m, n \leqslant 2r + 1$, and is the direction of the point. The direction features of the points are described in detail in the Part 1 of this Section.

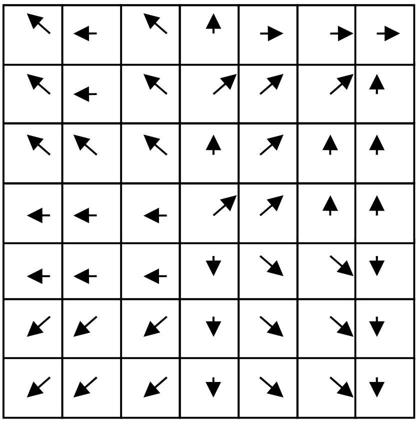
4) Traverse all edge points, repeat step (2) and (3). By this step, the statistical features of the direction features are obtained. With the increase of statistical number, the probability distribution of each location gradually tends stable, which can reflect the implicit features of the handwriting.

5) Normalization. The number of edge points in each image is not consistent, total number $\sum_{(m,n)} N(m, n)$ of all points in statistical process shall be used for normalization (where $N(m, n)$ is the sum of edge points appear in location (m, n)), the probability density value to obtain various encodings is

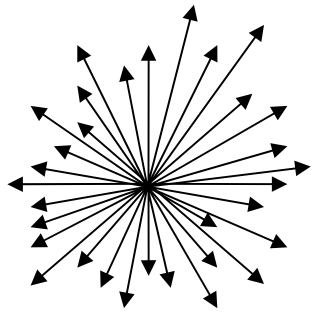
$$p(m, n, d_i) = \frac{N(m, n, d_i)}{\sum_{(m,n)} N(m, n)}\,, \tag{1}$$

Where, $N(m, n, d_i)$ is the sum of edge points appear direction d_i at the location (m, n).

Features obtained through a series of operations are shown as the LCDF feature in Fig. 5. The window size of feature is 7×7 in Fig. (a), each location contains eigenvector with 32 directions shown as Fig. (b), the main direction is only indicated in Fig. (a).



(a) 7×7 LCDF feature



(b) 32 direction features of each location

Fig. 5. Example of LCDF feature

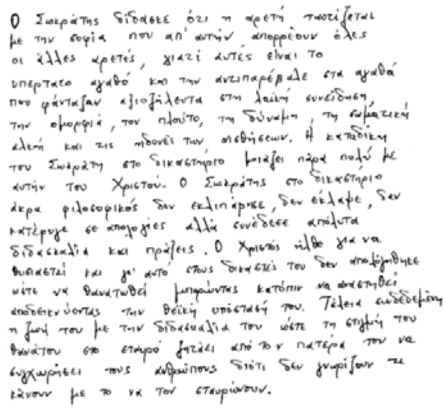
2.2. *Similarity measurement*

After obtaining the handwriting features, we tested a series of similarity measurement methods, including weighted Euclidean distance, weighted chi-square distance and weighted Manhattan distance. The weighted Manhattan distance shows higher performance in the test, so the weighted Manhattan distance method is chosen finally. The weighted Manhattan distance used between handwriting features and similarity measurement is defined:

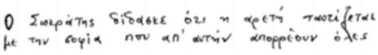
$$D = \sum_{i} \frac{|LCDF_{1i} - LCDF_{2i}}{\sigma_i} . \tag{2}$$

Where, $LCDF_{1i}$ and $LCDF_{2i}$ are respectively the i component of two LCDF features, σ is the standard deviation of the component of LCDF feature in all samples.

After obtaining the weighted Manhattan distance between the obtained features, we use the nearest neighbor principles for similarity measurement. That is to say, the smaller the distance between the two handwriting features, the higher the similarity, and the more likely it belongs to the same person's handwriting.



(a) Original



(b) Cropped

Fig. 6. Example of ICDAR2011 writer identification database

3. Experiment

We tested the performance of the proposed method in the database provided by the ICDAR2011 writer identification contest. ICDAR2011 writer identification contest is the first competition of the category algorithm, the test database used in the contest contains handwriting images of 26 testers, 8 pieces for each and the original database is constituted by a total of 208 images. The handwriting contains various languages such as English, French, German, and Greek. In addition, the test data also contains a cropped database, which has fewer characters in each image, and is used to test the performance of the algorithm when the handwriting information is less. Fig. 6 shows the two images in the database, the number of characters in the cropped database is much smaller than that in original database, which increases the difficulty of extracting stable features.

For each picture, we calculate its LCDF eigenvectors and then calculate the weighted Manhattan distance between the other image eigenvectors in the database.

Two measurement methods of soft (soft TOP-N) and hard (hard TOP-N) are used in performance test, which are two different statistical method of accuracy. Among them, the correct first choice, correct front 2, correct front 5 and correct front 10 (namely $N = 1, 2, 5, 10$) are selected in soft TOP-N. It indicates the accuracy that there is at least one and the image for query in the minimum distance with the feature of the image for query in matching belonging to the same writer. While in the hard TOP-N, the correct front 2, the correct front 5 and the correct front 7 are selected (namely $N = 2, 5, 7$). Since each handwriting has 8 images, the maximum is 7. It indicates the accuracy that all and the image for query in the minimum distance with the feature of the image for query in matching belonging to the same writer. Requirements of hard TOP-N are strict, and it is difficult to achieve higher accuracy.

Tables 1 to Table 4 show the performance of the proposed algorithm at different sizes of windows. With the change of sliding-window, the performance of the algorithm fluctuates slightly, but the range of change is very small, which shows good stability of the algorithm. Table 5 to Table 8 show a comparison of the proposed algorithm and other algorithms, the line 1 to 8 of these form is the performance of algorithm in ICDAR2011 handwriting contest, the line 9 is the performance of algorithm proposed in the Literature [6], and the last line is the performance of the algorithm proposed in this paper, the highest performance of each index is highlighted in bold. The reason why choose the Literature [6] for comparison is that this algorithm is used for counting the feature of the contours in sliding-window, which is similar to the algorithm in this paper. Both the algorithm in Literature [6] in Table 5 to Table 8 and the proposed algorithm in this paper adopt the window size of 13×13 to obtain more balanced performance. The experimental results show that although the performance of the algorithm is slightly behind the performance of the advanced algorithm on the original database, most of the indexes in the cropped database exceed the existing advanced algorithms.

Table 1. The window size and accuracy of proposed methods on original database (soft TOP-N code shall be used)

Window size	***TOP-1***	***TOP-2***	***TOP-5***	***TOP-10***
11×11	98.6%	98.6%	99.0%	99.0%
13×13	98.6%	98.6%	99.0%	99.0%
15×15	98.6%	98.6%	99.0%	99.0%

Table 2. The window size and accuracy of proposed methods on original database (hard TOP-N code shall be used)

Window size	***TOP-2***	***TOP-5***	***TOP-7***
11×11	94.2%	82.2%	46.2%
13×13	94.7%	83.7%	50.5%
15×15	95.7%	84.1%	50.0%

Table 3. The window size and accuracy of proposed methods on cropped database (soft TOP-N code shall be used)

Window size	***TOP-1***	***TOP-2***	***TOP-5***	***TOP-10***
11×11	94.7%	98.1%	98.6%	99.0%
13×13	95.7%	97.6%	98.6%	98.6%
15×15	95.2%	97.6%	98.6%	98.6%

Table 4. The window size and accuracy of proposed methods on cropped database (hard TOP-N code shall be used)

Window size	***TOP-2***	***TOP-5***	***TOP-7***
11×11	84.6%	57.2%	21.6%
13×13	88.0%	59.6%	22.6%
15×15	89.9%	62.0%	26.0%

Table 5. Comparison with other methods on original database based on soft TOP-N code

Method	***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%
Method of Literature [6]	98.6%	99.0%	99.0%	99.5%
Method of this paper	98.6%	98.6%	99.0%	99.0%

Table 6. Comparison with other methods on original database based on hard TOP-N code

Method	***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%
Method of Literature [6]	95.2%	82.2%	44.2%
Method of this paper	94.7%	83.7%	**50.5%**

Table 7. Comparison with other methods on cropped database based on soft TOP-N code

Method	***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%**
Method of Literature [6]	**95.7%**	97.1%	**98.6%**	98.6%
Method of this paper	**95.7%**	**97.6%**	**98.6%**	98.6%

4. Conclusion

In this paper, a method of writer identification based on Local Contour Direction Feature (LCDF) is proposed by using the idea of generality distribution. In the method, 32 direction categories of edge points are defined. These directions contain the trend of strokes so as to effectively recognize the handwriting of the handwriting. Taking the direction distribution probability of statistical strokes in sliding-window as features, and the complexity of encoding is reduced by using the method of superposition statistics. Finally, the weighted Manhattan distance is used to measure the difference between eigenvectors. The proposed method is easy to implement and has a good recognition effect in writer identification. The experiment demonstrates that the proposed method achieves the performance of the advanced algorithm in ICDAR2011 writer identification competition database[10]. And the experimental results show that most of the indexes of this method have reached the level of advanced algorithms. The performance of algorithm with less handwriting character is superior to other algorithms on the cropped database, which indicates that the proposed method can obtain the handwriting features with less character, and it is suitable for writer identification with less character, and has good prospects of practical application.

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