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Off-line handwritten biometric recognitionbased on stroke direction distribution features

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ABSTRACT

Off-line handwritten biometric recognition (OLHBR) is an authentication method based on writing features detected from differenthandwriting images. It remains a challenge for no dynamicwriting order can be used. In this paper, a method based on stroke direction distribution feature (SDDF) is proposed for OLHBR. The proposed feature is utilized for catchingthe distribution features of strokes, which are counted by a loop counting procedure. Then, the similarities between features are measured by the weighted Manhattan distance. In order to reduce the impact of the stroke thickness, two methods have been applied in our method. One is decomposing the whole contour into strokes. Another is ignoring the fragments not connecting the center pixel in a current loop counting window. At last, the experiments on ICDAR 2011writer identification database show the effectiveness of the proposed method.

KEYWORDS

Handwritten biometric recognition; Stroke feature; Stroke direction distribution feature; Weighted Manhattan distance.

INTRODUCTION

Handwritten biometric recognition, which is also called writer identification,is widelyused for identification in forensic and historical fields. The hypothesis of this application is that each person has their own writing style which can be characterized by the information presented in their handwritten patterns. So, handwritten biometric recognitionis a science and technology to judge the identification of a writer by analyzing and comparing the writing feature of different people.

According to the ways of obtaining handwritings, handwritten biometric recognition can be categorized into two groups: on-line and off-line[1]. In an on-line way,some special capture devices, such as tablets, are needed to catch the velocity of thepen movements which contains temporal information such that writing order and dynamics. While in an off-line way, only a scanner is used for obtaining writing images. So, off-line handwritten biometric recognition (OLHBR) is more popular. But it is a more challenging task for its lacking of temporal information. In this paper, the off-line way is concerned.

In the past years, many methods for OLHBR are proposed. Newell et al.[2]described a feature named oriented Basic Image Feature Columns for writer identification and enhanced their scheme by encoding a writer's style as the deviation. He et al.[3]extracted rotation-invariant features from images to perform writer identification. Kumar et al.[4] presented a sparserepresentation of handwritten structural primitives. Djeddi et al.[5]employed aset of run-length features in a multi-script environment. Bertoliniet al.[6]discussed the use of two texture descriptors (local binary patterns andlocal phase quantization) to perform writer verification and identification. Bulacu et al.[7] proposed a serial features with direction, angle for handwritten biometric recognition. Li et al. proposed a micro-structure feature[8], which makes good performances on Chinese character identification.

An OLHBR system should consist of two main parts: the representation of the writing image andthe similarity computation. The measurement of similarity, to some degree, is largely dependent on the features of the writing images. Therefore, the core task of OLHBR is to design an effective and discriminative feature. In this paper, a method based on stroke features is proposed for OLHBR.

This paper is structured as follows. Section 2 isthe feature abstraction and similarity measurement. The contour of a character, which contains local properties of the character, has been shown to be the most effective feature for handwritten biometric recognition. The contour is decomposed into strokes to reduce the impact of stroke thickness. The distribution of local structures can be used as the feature of handwriting. Using this idea, a feature based on stroke direction distribution feature is proposed. Edge pixels are divided into 32 categories to gain the directions of strokes. Direction features are counted in sliding windows and normalized into stroke direction distribution features (SDDF). In counting procedure, the fragments not connecting the center pixel are ignored. The weighted Manhattan distance is used as similarity measurement at last. Section 3 is the experiments. To evaluate our method, the ICDAR 2011 writer identification database with multi-languages is used in the experiments. The resultsshow that the proposed method gets the state-of-art performance. Finally, section 4 concludes our work and indicated some future directions.

THE SDDF ABSTRACTION AND SIMILARITY MEASUREMENT

There are two main parts in this section: the feature abstraction and similarity measurement. The feature abstraction procedure obtains the SDDF of each writing images. And the similarity measurement is used for judging the similarities among the SDDFs of the images.

The flowchart of feature abstraction is shown in Figure1. This procedure includes four steps: contour detection, contour decomposition, loop counting and normalization. Contour detection is the preprocessing. It obtained the contours which contains effective information for off-line writer identification. In our experiments, Sobel or Canny detector is used for contour detection. If the background of the image is homogeneous, the contour can be obtained by the Sobel detector. Otherwise, the Canny detector is more suitable. The whole contour is composed of several strokes and the ends of strokes are greatly influenced by stroke width. So, the contour is discomposed for reducing the impact of stroke width. Loop counting is the main step, which contains direction distribution counting. The normalization is a step of eliminating the statistical difference of writing images.

Contour decomposition

The contour has some negative structures for handwritten biometric recognition. As shown in Figure 2(b), the stroke thickness has great influence on contour. With different stroke thicknesses, even the same writer has different writing features. In order to reduce this negative impact, the contour is decomposed into fragments for feature abstraction. As shown in Figure 2(c), fragments are more similar than contours.

The ends of strokes are more sensitive in different stroke thickness conditions. So our method decomposed a contour into fragments at its ends. The contour segmentationis followed next steps.

1. Corner detection on contour. Most end structures of strokes are corners. The detector applied in this step is a disk template and its radius is about two or three times of the stroke thickness. Then, the number of stroke pixels connect the center edge pixel is counted. If the number $N$is over a threshold t, the current pixel is a corner.

2. Local minimum detection. There are too many corners in the first step. This step will suppress most of them.

3. The edgesnear the ends of strokes may be distorted and can not represent the direction features. Therefore these pixels directly connecting the minimum positions in their neighborhoods are excluded in the counting procedure.

4. Excluding the short fragments. These fragments are little valuable for handwritten biometric recognition. As shown in Figure 2(c), the obtained fragments are stroke used in the following steps.

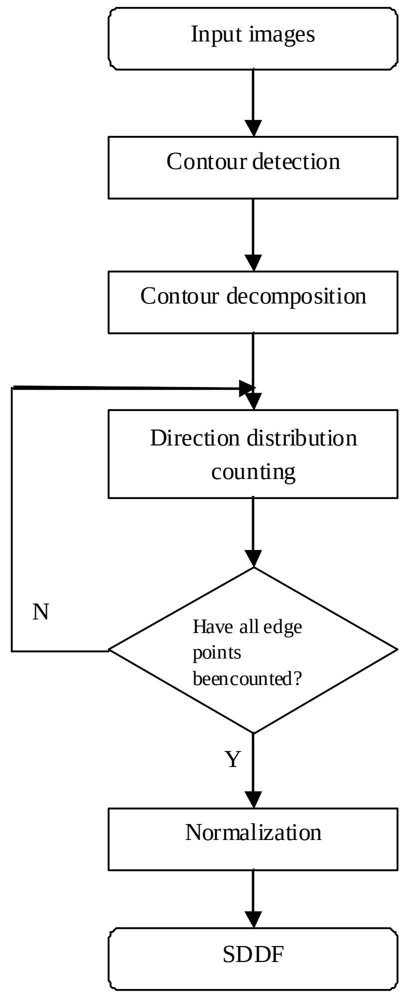


Figure 1 : The flowchart of the SDDF abstraction.

(a) Original characters (b)Contours (c)Strokes

Figure 2 : Two characters with different stroke thicknesses.

Fragment direction feature

Direction is an important feature for handwritten biometric recognition. The start, handling and end of the stroke contain the direction features. Based on this principle and the idea of distribution, a stroke direction feature is proposed for handwritten biometric recognition.

By analyzing the structure of handwriting, a feature in a 5×5 window is defined. As shown in Figure 3, the feature contains 32 categories. The center black dots represent current edge pixels and other black dots are edges in the neighborhoods. An edge pixel may have several directions.

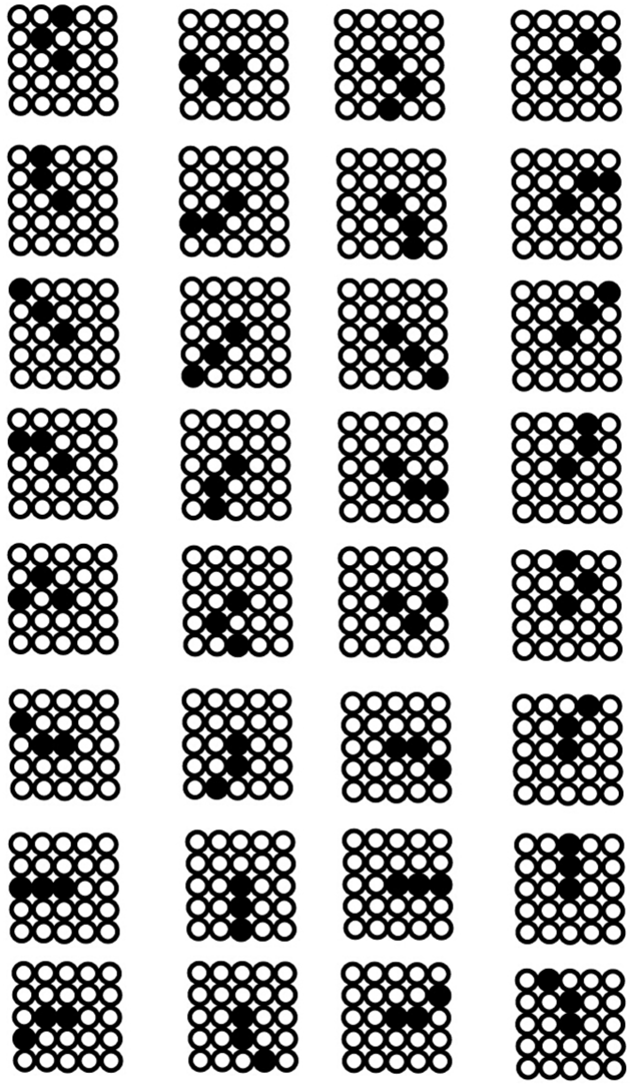


Figure 3 : Thirty two directions in a 5×5 window.

The feature abstraction

The distribution of direction features can represent the stroke directions. But it is too small to have reliable performance. Therefore, a possible method is counting features in a wider range. The whole SDDF abstraction contains next steps:

1. Contour detection. It is a preprocessing of feature abstraction. We used Sobel detector in this step. If images with complex backgrounds are processed, Canny detector may be more useful.

2. Contour decomposition. This step decomposes the contour at end structures. This is a step for reducing the impact of stroke thickness.

3. Local fragment abstraction. It is another method applied in feature abstraction for reducing the impact of stroke thickness. The rectangle in Figure 4(c)is a sliding window whose size of the window is$(2r+1)\times(2r+1)$. Its center is the current edge pixel marked with'x'. There may be several fragments in the window, which are parts of the contour. Only the fragment connecting the center is counted in literature[9]. We also applied this method for reducing the impact of different stroke thicknesses. Figure 4 shows an example of local fragment extraction procedure. There are two fragments in the window and only the one connecting center pixel is used in next step.

4. Counting the number of (m, n, d_i), where (m, n) is the position in a sliding window, $1 \leqslant m, n \leqslant 2r+1$, and d_i is a category of 32 directions.

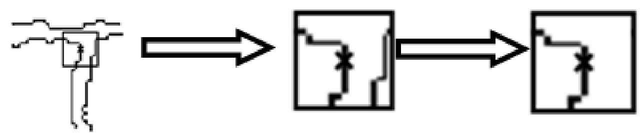
5. Repeat step 3 and 4 until all edge pixels are counted.

6. Normalization. The edge pixel numbers of different images are not same. So, the distribution is dividedby $\sum_{(m,n)} N(m,n)$, where $N(m,n)$ is the number of edge pixels at position (m,n) in sliding windows. Then, the probability density of the feature is defined as

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

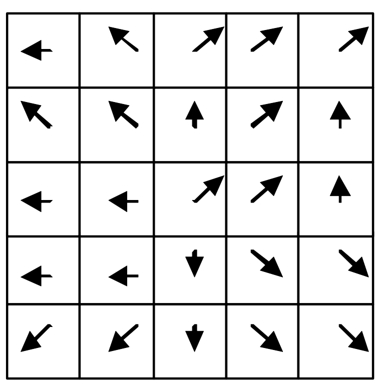
where $N(m,n,d_i)$ is the number of edge pixels with direction $d_i$at position (m,n).
The obtained SDDF is shown in Figure 5. The size of example window show in Figure 5(a) is 5×5, each site contains the probability densities of the thirty two directions as shown in Figure 5(b). So the SDDF shown in Figure 5 is a vector with 32×25 elements.

(a) Original characters (b)Contours

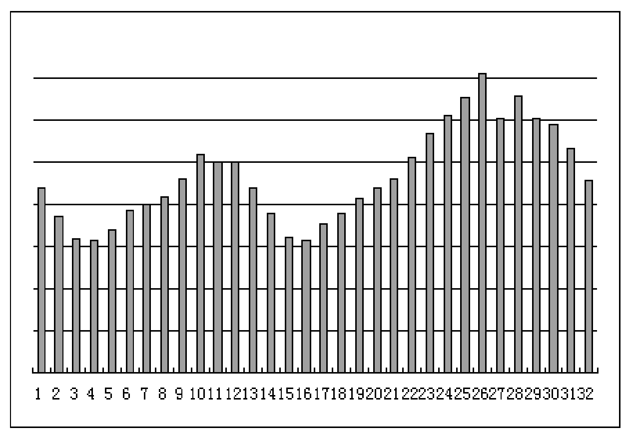


(c) Fragment extraction

Figure 4 : Fragment used in a sliding window



(a) An example of SDDF.



(b) The vector of one site.

Figure 5 : An example of SDDF

Similarity measurement

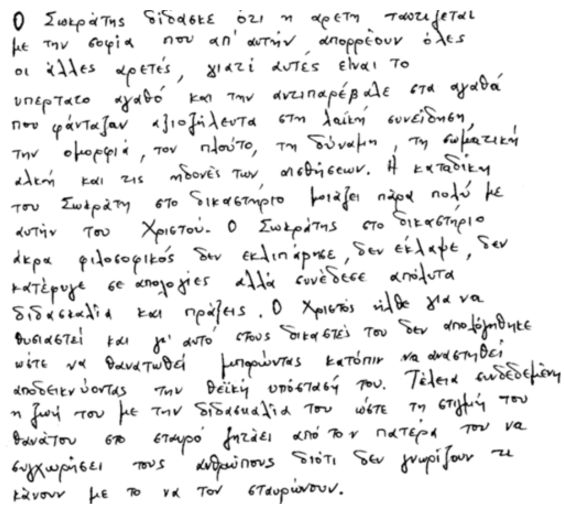
In our experiments,several methods have been applied for distance measurements. Among them, the weighted Manhattan distance obtained the best performance, whose definition is

$$D = \sum_i \frac{|SDDF_{1i} - SDDF_{2i}|}{\sigma_i}, \quad (2)$$

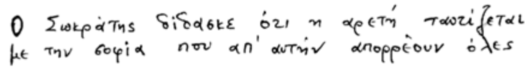
where σ_i is standard deviation of the ith component of SDDFs,$SDDF_{1i}$ and $SDDF_{2i}$ are the ith components of correspondingSDDFs, respectively. The nearest rule is used in similarity measurement. That is, smaller the distance, more similar between the two images.

EXPERIMENTS

To evaluate the effectiveness of the proposed method, we testedit on ICDAR 2011 writer identification database[10]. This database isconsisted with 26 writers and each writer has eight pages. There two different evaluations. The first uses the original images while the seconduses the cropped images. Figure 6 shows two examples. A cropped image has only two lines while anoriginal image has almost a page of characters. It is more difficult to abstract stable features from few characters. So, handwritten biometric recognition on cropped images is more challenging.



(a) An example of original image.



(b) An example of cropped image.

Figure 6 : Examples of ICDAR2011 writer identification database.

The SDDFs of imageswere abstracted andthe weighted Manhattan distance was calculated between every two SDDFs. Then, results were sorted from the most similar to the less similar. The performanceis evaluated by two different measurements, soft TOP-N and hard TOP-N criterion. The soft TOP-Nis the accuracy of at least one of the same writer is included in the N most similar images. While the hard TOP-N criterion is the accuracy of all the N most similar images are written by the same writer.

TABLE 1-4 show the performance of the proposed method with different sliding window sizes. The results show the stability of the proposed method. TABLE 4-8 show the comparisons of the proposed method with othermethods where line 1-8 are methods mentioned in ICDAR 2011 and line 9 is the method proposed in[8]. In TABLEs 4-8, the highest accuracy results are marked in bold. The size ofsliding window used in TABLEs 4-8 is 13×13. Though theperformance of the proposed method on original images is slightlybelow the highest, its performance on cropped images exceed theexisting methods.

TABLE 1 : The performance with different window sizes on original images (soft evaluation).

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

TABLE 2 : The performance with different window sizes on original images (hard evaluation).

Window size	**TOP-2**	**TOP-5**	**TOP-7**
11×11	92.8%	78.3%	43.8%
13×13	93.3%	81.3%	49.0%
15×15	93.8%	80.8%	45.2%

TABLE 3 : The performance with different window sizes on cropped images (soft evaluation).

Window size	**TOP-1**	**TOP-2**	**TOP-5**	**TOP-10**
11×11	93.8%	98.6%	98.6%	98.6%
13×13	96.2%	97.6%	98.6%	98.6%
15×15	93.8%	96.6%	98.1%	98.6%

TABLE 4 : The performance with different window sizes on cropped images (hard evaluation).

Window size	TOP-2	TOP-5	TOP-7
11×11	82.2%	49.0%	18.8%
13×13	85.1%	51.0%	15.9%
15×15	86.1%	52.4%	18.8%

TABLE 5 : Soft evaluation using originalimages of ICDAR database.

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%
The method of [8]	98.6%	99.0%	99.0%	99.5%
The proposed method	98.6%	98.6%	99.0%	99.0%

TABLE 6 : Hard evaluation using originalimages of ICDAR database.

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%
The method of [8]	95.2%	82.2%	44.2%
The proposed method	93.3%	81.3%	49.0%

TABLE 7 : Soft evaluation using croppedimages of ICDAR database.

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%
The method of [8]	95.7%	97.1%	98.6%	98.6%

The proposed method	96.2%	97.6%	98.6%	98.6%

TABLE 8 : Hard evaluation using croppedimages of ICDAR database.

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 method of [8]	85.1%	51.0%	16.8%
The proposed method	85.1%	51.4%	15.9%

CONCLUSION

In this paper, a method based on SDDFhas been proposed. Inorder to reduce the impact of stroke thickness, the contour was decomposed into strokesand only the fragmentsconnecting the centers in sliding windows were counted. TheSDDFwas extracted from the slidingwindows by counting the stroke direction distributions. The loop countingprocedure was an easy way to be implemented, whose main part was a repeated operation of addition. Lastly,the weighted Manhattan distance effectively measured thesimilarities betweenevery twoSDDFs. The experiments on theICDAR database showed the excellent performance of the proposed method.

In the future, the worth investigated aspect is to obtain some discriminative features with large scales to overcome some shortcomings of local features. We plan to enlarge the window size of SDDF and replace the contour points by some significant points. In the future, some other similarity measurements should also be investigated for better classification performance.

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