Hierarchical Shape Primitive Features for Online Text-independent Writer Identification

Bangy Li, Zhenan Sun and Tieniu Tan
Center for Biometrics and Security Research, National Lab of Pattern Recognition,
Institute of Automation,Chinese Academy of Science,P.R.China
{byli, znsun,tnt}@nlpr.ia.ac.cn

Abstract

This paper proposes a novel method to text-independent writer identification from online handwriting. The main contributions of our method include two parts: shape primitive representation and hierarchical structure. Both shape primitive's features are developed to represent the robust and distinctive characteristics of handwriting in two hierarchies. In first hierarchy, the shape primitives probability distribution function (SPPDF)is defined as the static features, to characterize orientation information of writing style. For each shape primitive, the statistics of pressure is defined as the dynamic shape primitives probability distribution function (DSPPDF) and the second hierarchy we build Gaussian model in dynamic attributes (DA) according to curvature of shape primitives. Experiments were conducted on the NLPR handwriting database collected from 242 persons. The results show that the new method achieves high accuracy, fast speed and low requirement of the amount of characters in handwriting samples. We achieve a writer identification rate of 91.5 % with datasets in Chinese text and 93.6 % in English text.

1. Introduction

With fast development of pen-enabled electronic devices such as smart phone, PDA and Tablet PCs, temporal handwriting signals including pen-position, pen-down or pen-up, pen-pressure, pen-altitude, pen-azimuth at each sampling time can be recorded online. These terminals offer different features ranging from interpreting basic pen interactions to storing and managing of electronic ink documents and pen annotations [3]. Secure and automatic personal identification is becoming an important problem. Writer identification using handwriting, a behavioral biometric, is based on the observation that people write uniquely and can be characterized based on the information present in their handwriting. Automatic writer identification systems can be useful in a variety of applications including banks, criminal justice systems, determining the authenticity of handwritten documents, etc.

Traditionally, research into writer identification has been focused on two streams: offline and online writer identification [6]. Online handwriting allows us to use temporal information such as velocity, pressure and spatial information, which are not available in offline documents. Scarce research results can be found in the online text both Chinese and English for person identification. Recently, a number of new approaches to writer identification have been proposed. Pitak et al.[12] propose online writer recognition for Thai based on velocity barycenter of pen-point movement. Namboodiri et al. [9] propose a text independent writer identification framework that uses a specified set of primitives of online handwritten data to ascertain the identity of the writer. Yasushi et al.[13] propose an HMM-based text-indicated writer verification method, which is based on a challenge and response type of authentication process. In this method, a different text including ordinary characters is used on every occasion of verification. Liwicki et al.[7] use two sets of features extracted from a text line, the GMMs are trained using two sets of feature: point-based features and stroke-based features.

In this paper we address the problem of writer identification using online independent text. We present writer identification methods that use shape primitives in writing behavior of an individual. Our methods operate at two hierarchies: In the first hierarchy, we combine SPPDF and DSPPDF to get the ordered list of writer (rank 30) and in the second hierarchy we use an appropriate distance measure between the feature vectors in dynamic attributes (DA) according to curvature of shape primitives.

The paper is structured as follows. The next section presents motivation. Feature extraction is presented in Section 3. In Section 4 we describe the hierarchical structure of writer identification. The results of our experiments and discussion are presented in Section 5. Finally, in Section 6

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we conclude the paper.

2. Motivation

Our previous works [14][4] use 12 primary stroke types to indicate the writing style of the writer and build the stroke's probability distribution function (SPDF) of four dynamic features to writer individuality, which aims to capture distribution of more dynamic aspects of the writing behavior of an individual. This work need a number of characters to acquire more information in strokes and and it is difficult to define stroke types in Chinese text and can not work in different scripts. The method proposed by Bulacu et al [8] mainly focus on offline that have not dynamic features and the method proposed by Liwicki et al [7] do not consider statistical attributes in distribution of primitives in handwriting.

We present a hierarchical structure in shape primitive features using elementary primitives that contain more information in handwriting to identify writer. Online handwriting have more information than offline handwriting in dynamic attribute. Firstly we use distribute of shape primitives in handwritten text to characterize orientation of writing trajectory and distribution of dynamic shape primitives in pressure to characterize writing rhythm in shape primitives. Secondly, we use the hierarchical structure to search the ordered list of similar writer, Finally dynamic attributes (DA) (pressure, velocity, etc) in shape primitive are to characterize more detailed information of writing trajectory.

This method effectively uses shape primitives that contain more information for writing style which uses hierarchical structure of statistical features of primary primitives types and dynamic attribution in handwriting.

3. Feature Extraction

Our handwriting data is collected by Wacom Intuos2 tablet [2] which can be encoded as time-varying parameters such as x and y components concerning the pen-position at time t_i, the status of pen-down or pen-up s, the pen-pressure pr, the pen-altitude ϕ and pen-azimuth φ, and the raw handwritten data is represented as $\{x, y, t, s, pr, \phi, \varphi\}$ at each sampling point.

However, due to the high sampling rate of the tablet PC, some sample points mark the same trajectory points, especially when the pen movement is slow, the pen-tip is within 6mm (0.25 inch) distance from the tablet surface or some noise for handwritten text is recorded. After data acquisition, preprocessing is necessary to enhance the input data accuracy. Several signal processing algorithms for preprocessing can be used, and the preprocessing of an online handwritten data generally consists of filtering in order to remove spurious signals or noise from the text.

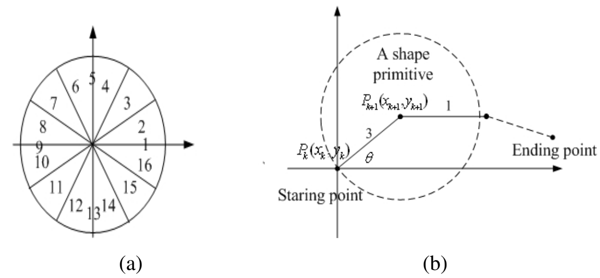

Figure 1. Primitive of handwriting (a) Model of direction. (b) A shape primitive in a stroke.

3.1. Feature Extraction with SPPDF

We extract static features based on strokes that mean a connected component from pen-down to pen-up. Thus a stroke is a sequence of points during a certain time interval between the time when the pen-tip touches the panel to the time it leaves. According to writing direction of each point in strokes, we define 16 angles including 12 directions and two vertical and two horizontal directions as direction model as Fig. 1(a) shows, then we define shape as direction types in two points and angle computed by

$$\theta = \arctan\left((y_{k+1} - y_k)/(x_{k+1} - x_k)\right) \qquad (1)$$

Therefore two directions (three points) form a shape primitive and a large number of shape primitives (as Fig. 1(b) shows) can be derived from each handwriting sample, the shape primitives can cover over all strokes according to the direction models and primitives sequence is extracted from the whole handwriting data. The total number of primitives consist of $(16 * 16)$ primitives, Fig. 2 shows 256 types primitives.

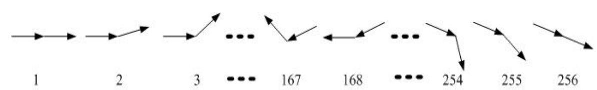

Figure 2. The type of primitives .

Bulacu etc [8] propose the edge-based directional probability distributions in offline handwriting which have been proven to be effective for off-line writer identification. However, in online handwriting data primitives contain shape attribute and writing sequence in trajectory of handwriting which can represent habit of writing. We use shape primitives probability distribution function (SPPDF) as the shape features $(f1)$ to characterize writer characteristics. The distribution of shape primitives P(,.,) capture both the orientation and curvature of contours, which can also be interpreted as the transition probability between primitives in

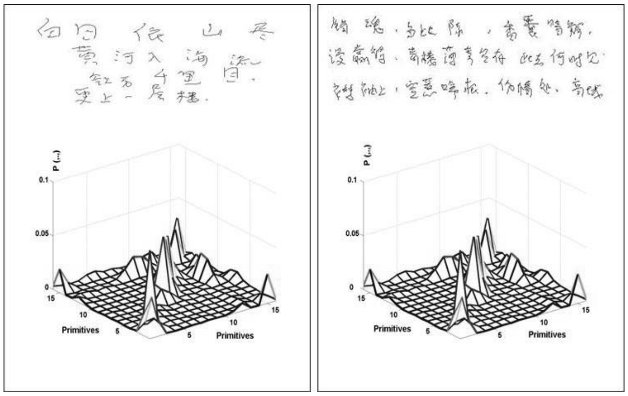

Figure 3. Illustration of shape primitives probability distribution function in Chinese texts by a writer.

a simple Markov process. Fig. 3 illustrates shape primitives probability distribution function in Chinese text by a writer.

3.2 Feature Extraction with DSPPDF and DA

Online handwriting data is recorded as time-varying parameters. We define four dynamic attributes ($\overline{pr}$,$\overline{\phi}$,$\overline{\varphi}$,C) as Fig. 4 shows.

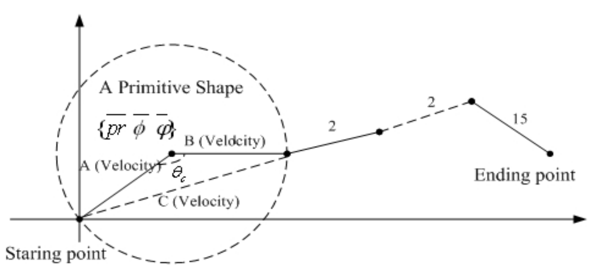

Figure 4. The type of shape primitives .

- $\overline{pr}$: Average pressure change of three point in primitives
- $\overline{\phi}$: Average altitude of three point in primitives
- $\overline{\varphi}$: Average azimuth of three point in primitives
- C: Length or velocity of C in primitives

For $\overline{pr}$ attribute, we use dynamic shape primitives probability distribution function (DSPPDF) in pressure attribute as the feature ($f2$) to characterize writing trajectory, the number of histogram bins in $\overline{pr}$ spanning the interval 0-1024 was set $N = 2$ to through experimentation: 2/bin gives a sufficiently detailed and sufficiently robust description of handwriting and we select the effective bins (100 dimensions) to be used in writer identification. Fig. 5 illustrates dynamic shape primitives probability distribution function ($f2$) in Chinese text by a writer.

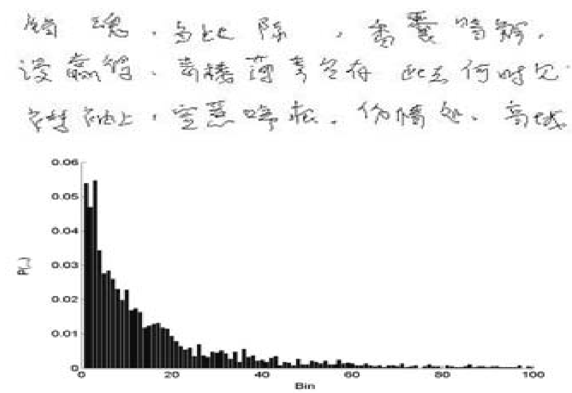

Figure 5. Illustration of dynamic shape primitives probability distribution function (f2) in Chinese text by a writer.

Angle θ_c can be derived by the following trigonometric formula:

$$\theta_c = \arccos\left((A^2 + B^2 - C^2)/(2 * A * B)\right) \qquad (2)$$

where θ_c represents the curvature of the shape primitives of online handwriting and is quantized in 18 bins: the angle 10^0/bin. Feature ($f3$) uses the mean and variance value of four dynamic attributes (DA) ($\overline{pr}$,$\overline{C}$,$\overline{\phi}$,$\overline{\varphi}$) in each bin and thus get a sequence of 18*4*2 dimensional feature vectors which can be used for writer identification.

An overview of all the features used in our study is given in Table.1. In our analysis, we will consider three features based on shape primitives that we have designed and used for writer identification.

Table 1. Overview of the considered features.

Feature	Explanation	N dimensions
$f1$	Shape primitives	256
$f2$	Dynamic shape primitives	100
$f3$	dynamic attributes	144

4 Hierarchical Structure for Writer Identification

We use hierarchical structure for writer identification which is performed using the the nearest neighbor classifier in a "leave-one-out" strategy. A large of number of distance measures are tested in our experiments: L1, L2, Cosine-Angle (CA), Chi-Square (CS) and Diffusion-Function (DF) distances [10] [11] [5]. Only the best performing ones (DF) are reported. For online text-independent write identification, In first hierarchy, we use simple (average) fusion in SPPDF and DSPPDF to return the ordered list of writer (30 candidates) and then in the list an appropriate distance measure between the feature vectors in curvature of the shape primitives is computed to identify writer. Fig.6 shows a hierarchical structure in shape primitives for writer identification.

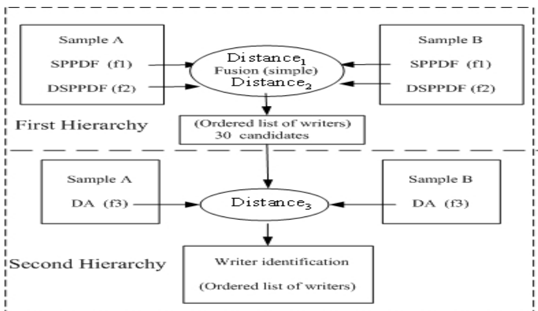

Figure 6. A hierarchical structure for writer identification.

5 Experimental Results and Discussion

Our experiments are based on the NLPR online handwriting database [1], which contains more than 1500 handwritten texts in online format from over 242 writers in two sessions. In collecting data process, we require the writer writing text in normal situations and habits of writing style. Each writer writes eight pages of texts which include four pages of Chinese texts and four pages of English texts respectively. In the first session, each writer has written the same sentence of about 50 Chinese and English words in one page respectively and different Chinese and English sentences about 50 words in two pages respectively. In the second session, each writer has written different Chinese and English sentence about 50 words in one page respectively. In the section we report a number of experiments with the database. Therefore, our databases contain three sub-datasets: dataset I (DB I)includes two session in Chinese text. Dataset II (DB II) includes two sessions in English. We merged Chinese and English dataset to obtain dataset III (DB III).

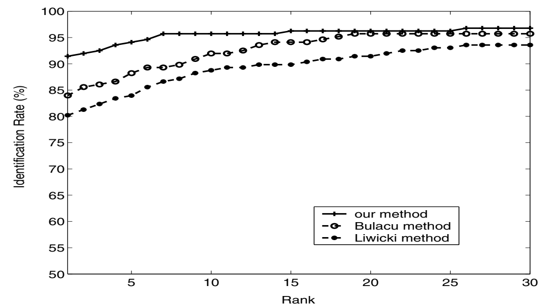

Figure 7. Average performance of writer identification in different Chinese templates as a function of rank size for Chinese text.

5.1 Experimental Results

Table.2 gives the average performance of the writer identification in individual features between same texts as template and different texts as template in different databases.

Table 2. Features Vs Accuracy In Different Databases

	Chinese database		English database	
Features	Rank 1	Rank 5	Rank 1	Rank 5
$f1$	82	89	83	91
$f2$	35	62	40	65
$f3$	62	80	65	81

For DB I (Chinese Database). Firstly, we use same Chinese texts as templates, different Chinese texts as testing samples, then we also use different Chinese texts as templates and different Chinese texts as testing samples. Fig.7 gives average performance of the writer identification in different Chinese templates based on Chinese text. For DB II (English Database). Fig.8 gives average performance of the writer identification in different English templates based on English text.

5.2 Discussion

Form the experimental results, a number of observations can be made. As Table.2 shows, it is important to observe that feature f1 performS much better than the others and the performance of writer identification in English text is better than Chinese text. The main reason for this result is that English text contain more information of orientation than Chinese text. For English text, we define 18 angles that do not contain two vertical and two horizontal directions

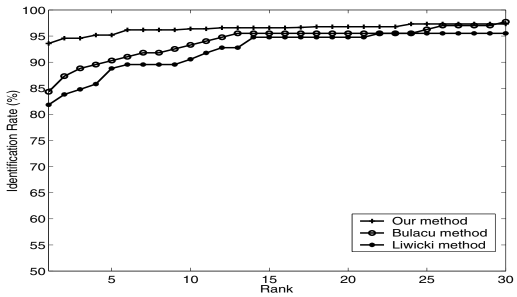

Figure 8. Average performance of writer identification in different English templates as a function of rank size for English text.

as direction model depending on the different characteristic between English and Chinese text.

Second, Fig.7 and Fig.8 show our method using hierarchical structure in shape primitives is better than other methods. The method proposed by Bulacu et al [8] do not consider dynamic features ($f1$ feature is similar to Bulacu method) and combination of the orientation information and dynamic shape primitives. Our use hierarchical structure effectively to fusion dynamic and static features in writer identification.

The method proposed by Liwicki et al [7] shows better performance of writer identification in English text, In our experimental results, our method is better than Liwicki method that need an amount of characters (about 160 characters) to train GMMS and about 80 characters to validate parameters of GMMs. Our method can improve performance and reduce an amount of characters.

At last, for behavioral biometric, the robust features depend on emotions and physical state of writer. We use statistical features to overcome instability of the writing and then exploit dynamic features according to curvature of shape primitives. In future work we focus on cross-language (English & Chinese) writer identification.

6 Conclusions

In this paper, we have proposed a novel method based on hierarchical structure of shape primitives for online text-independent writer identification. It is an important attribute that shape primitives are to characterize orientation in writing style and dynamic shape primitives present distribution of writing rhythm in shape primitive. We combine the static and dynamic feature of shape primitive to characterize attribute of shape primitives in writing trajectory and then dynamic attribute in curvature of shape primitive. Experimental results show that our method are very stable personal characteristics, reveal individual writing style and improves the identification accuracy and reduces the amount of characters required.

Acknowledgments

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