A New Method for Rotation Free Online Unconstrained Handwritten Chinese Word Recognition: A Holistic Approach*

Kai Ding, Lianwen Jin*, Xue Gao
College of Electronic and Information, South China University of Technology, Guangzhou, PRC
**E-mail eelwjin@scut.edu.cn*

Abstract

Most online handwriting word recognition (HWR) approaches proceed by segmenting words into isolate characters which are recognized separately. Inspired by results in cognitive psychology, holistic word recognition approaches provides another effective way to deal the problem of HWR. In this paper, we propose a new method for rotation free online unconstrained Chinese word recognition through a holistic approach. By a gravity center balancing skew detection and correction method, the rotation ranging from 0° to 360° of a Chinese handwritten word can be detected. Through the process of preprocessing, feature extraction using elastic meshing technique and classification, the handwritten words with characters even connected or partially overlapped can be recognized through a holistic approach. Experiments were performed on 8888 categories of 1,137,664 unconstrained handwritten Chinese word samples. Experimental results for randomly rotated unconstrained cursive handwritten Chinese word data demonstrated that the proposed method can achieve about 96.58% recognition accuracy.

1. Introduction

With the increase in popularity of portable computing devices such as PDAs and mobile phones, non keyboard based methods for data entry are receiving more attention in the research communities and commercial sector. It motivates the development of online handwriting recognition technology [1][2]. However, most Chinese handwriting input methods in the market are based on recognition of single character. As the single Chinese character recognition has been solved at a certain extent, it would be advisable that more efforts be paid on the research of Chinese word recognition. Great progress has been achieved in the field of HWR of western language [3][4] during the past decades, but the issues of Chinese HWR is less investigated in the literature [5].

Generally, HWR has traditionally been tackled by using two main approaches: the analytic approach and the holistic approach [6]. In the former approach, the word is treated as a collection of simpler subunits such as characters, and typically recognized by segmenting the word into subunits and identifying the subunits to obtain a word-level interpretation. The latter approach treats the word as a single, indivisible entity and attempts to recognize it using features of the word as a whole [7]. This approach is inspired by psychological studies of human reading, which indicate that humans seldom read letter by letter; they use holistic features of the word shapes such as length, ascenders, descenders and loops to read whole words at once.

The advantage of holistic approach are manifolds: (1) It can avoid the segmentation procedure which is a challenging problem in the analytic approach; (2) Holistic features provide information about the word that is orthogonal to the knowledge of characters and may succeed when the writing is so poor that the individual characters cannot be distinguished but the overall shape of the word is preserved [6]. (3) Moreover, researches reveled that combining holistic and analytic approaches can improve the recognition rate over that of a single classifier [8], so these two approaches can be considered complementary.

Inspired by all of these, a number of studies have been performed on holistic HWR approach [6][7][9][10]. Sriganesh Madhvanath and Venu Govindaraju [6] summarized the potential role of the holistic paradigm in offline handwritten English word recognition. Jose Ruiz-Pinales et al.[7] also proposed a holistic offline word recognition algorithm based on perceptual feature extraction. And holistic Arabic and Brazilian word recognition are proposed in reference [9] and [10] respectively.

* This paper is partially sponsored by the following research projects: NSFC (no. U0735004, 60772116), GDNSF (no. 07118074).

978-0-7695-3725-2/09 $25.00 © 2009 IEEE
DOI 10.1109/ICDAR.2009.30

However, most of previous work deals with holistic offline Latin word recognition and few literatures can be found focused on holistic online Chinese word recognition. In this paper, we propose an effective solution for the problem of rotation free online Chinese word recognition through a holistic approach. By implementing a novel gravity center balancing method [5], the rotation ranging from 0° to 360° of handwritten words can be detected. Then preprocessing and feature extraction based on elastic meshing technique are employed to extract the directional feature of the whole word. Finally holistic feature is recognized by the classifier. Experiments were performed on 8888 categories of 1,137,664 unconstrained handwritten Chinese word samples collected with Pocket PC. The experimental results demonstrated the effectiveness of the proposed method.

The rest of this paper is organized as follows: the elastic meshing techniques is presented in Section 2. And our proposed holistic word recognition method and all of experiments are described in Section 3 and Section 4 respectively. Finally, the conclusions are summarized in Section 5.

2. Elastic meshing

Nonlinear shape normalization (NSN) [11] is the most widely applied method to solve the stroke location and shape variability of intra-class character in handwriting character recognition. On the other hand, the elastic meshing (ELM) technique [12] proposed by LW. Jin et al is considered as a suitable replacement for NSN in handwriting recognition. In the proposed holistic word recognition method, the ELM technique is employed and the performance of the ELM and NSN are compared in section 4.2.

ELM is the non-uniform region partition for character images with imaginary grids. Its principle is that after partitioning, adjacent regions should have equal number of character pixels. In general, let N be the width and height of the image, N_1, N_2 be the number of lines in horizontal direction and vertical direction respectively. For the elastic meshing lines in horizontal and vertical directions I_i and J_j, the equations (1-2) should be satisfied:

$$\int_1^N \int_{I_i}^{I_{i+1}} f(x,y)\,dx\,dy = \int_1^N \int_{I_k}^{I_{k+1}} f(x,y)\,dx\,dy \qquad (1)$$

$$\forall i,k = 1,2,3,\ldots,N_1 - 1$$

$$\int_{J_j}^{J_{j+1}} \int_1^N f(x,y)\,dx\,dy = \int_{J_k}^{J_{k+1}} \int_1^N f(x,y)\,dx\,dy \qquad (2)$$

$$\forall j,k = 1,2,3,\ldots,N_2 - 1$$

It is well known that the principle of NSN is that, the original character image is mapped into another one, in which the distribution of the histogram is equalized. In contrast to NSN, the ELM technique equally compartmentalizes the distribution of the histogram by constructing un-uniform grids. Both of these two methods can shape and standardize the images of handwritten word and intolerant the word's local deformation and stretching. But the shape of word is disturbed by NSN method while the word's shape is preserved for ELM technique.

3. Proposed Method

The overall flowchart of our method is shown in Figure1. In the following subsections, we explain in detail how each module works.

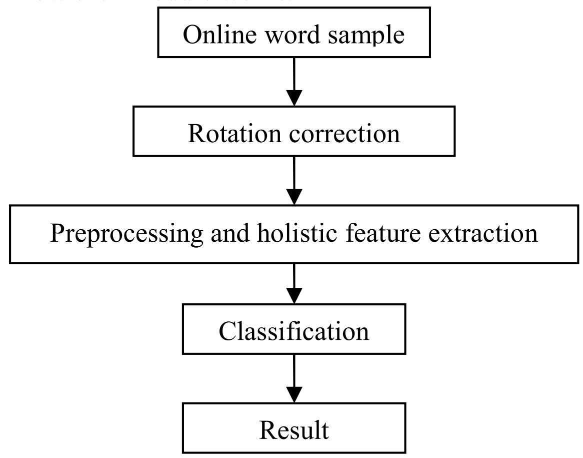

Figure1. **Overall flowchart**

3.1 Rotation correction method by gravity center balancing

Rotation correction is important in unconstrained handwritten word recognition because most character based recognition methods are not designed for rotation free. The tolerant rotation range of Chinese characters for those methods is usually within only ±10°[5].

In this paper, we use the gravity center balancing method proposed by Teng L, and LW. J [5] for rotation correction of cursive handwritten Chinese word. The method is described as follows:

1) Partition the word into left and right parts by the vertical line through the gravity center of the word. Calculate the gravity centers for each part.
2) Calculate the angle θ of the line which connected the two gravity centers in relation to horizontal line. If $\theta<\tau$ or $(180^\circ-\theta)<\tau$, where τ is a predefined threshold, then go to Step 5.
3) Rotate the word clockwise by the angle θ if $\theta<90^\circ$, or anti-clockwise by the angle $(180^\circ-\theta)$ if $\theta>90^\circ$.
4) Go to Step 1.
5) Partition the word into left and right parts by the vertical line through the gravity center of whole

word. If the starting point of the handwriting falls in the right part, rotate the word 180º clockwise.

6) Correct up-down reversed word.

A typical process of the rotation correction method is shown in Figure 2.

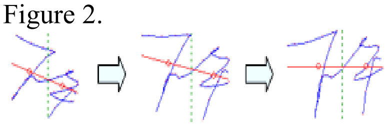

Figure2. **Rotation correction method.**

From the process of this method, it can be found that this method is based on an assumption that the gravity centers of most of words' left and right parts are on a horizontal line orientation.

To certify the correctness of this assumption, we conduct an experiment on 1,117,114 unconstrained Chinese word data, which are collected with normal handwriting mode and no additional rotation is applied. The procedure is as follows:

(1) Partition the word into left and right parts by the vertical line through the gravity center of the word. Calculate the gravity centers for each part.

(2) Calculate the inclined angle θ of the line which connected the two gravity centers in relation to horizontal line.

(3) Compute the statistical distribution of θ.

The result is shown in Table1.

Table1. **Statistical distribution of θ**

Range of θ	Proportion (%)
$0 \le \lvert\theta\rvert < 3°$	50.65
$3 \le \lvert\theta\rvert < 5°$	22.00
$5 \le \lvert\theta\rvert < 10°$	22.12
$\lvert\theta\rvert \ge 10°$	5.23

From Table1, we can see clearly that the proportion of the word, whose inclined angle θ ranges from -10° to +10°, is about 94.77%. This indicates that most of handwritten Chinese word samples satisfy the assumption that the centroids of left and right part of a word are on a horizontal line orientation. In addition, an experiment is designed to evaluate the performance of this rotation correction method in section 4.3. The results demonstrate that this rotation correction is very effective on rotated handwritten Chinese word samples.

3.2 Preprocessing and feature extraction

The feature we employed in this paper is the 8-directional feature proposed by ZL. Bai and Q. Huo[13]. We replace the nonlinear shape normalization (NSN) with elastic meshing (ELM) technique. The method is described as follows:

1) Linear normalization: the original character trajectories are normalized using an aspect-ratio preserving linear mapping. In isolated character recognition, the normalized size is fixed; however, in this paper we preserve the original aspect ratio of the word while fix the normalized height is 64.

2) Adding imaginary strokes: all successive real strokes are connected, and the trajectories between connected successive real strokes are considered as imaginary strokes.

3) Re-sampling: The sequence of online points in each stroke (including all imaginary strokes) of a character is re-sampled by a sequence of equidistance points.

4) Smoothing: the trajectory sequence is smoothed by a mean filter.

5) Extract the directional vector of each trajectory point: Assume point P_j is a random trajectory point, and its direction vector $\vec{V_j}$ is defined as follows:

$$\vec{V_j} = \begin{cases} \overrightarrow{P_j P_{j+1}} & \text{if } P_j \text{ is a start point} \\ \overrightarrow{P_{j-1} P_{j+1}} & \text{if } P_j \text{ is a non-end point} \\ \overrightarrow{P_{j-1} P_j} & \text{if } P_j \text{ is an end point} \end{cases} \quad (3)$$

6) Projection: the directional vector is projected to 8 directional axes to generate an 8-dimensional direction code at each trajectory point.

7) ELM: we divide the character image into 8×16 sub-blocks using ELM technique.

8) Blurred: Within each sub-block, the 8-dimensional direction codes are blurred by a Gaussian filter, resulting in a 1024-dimensional feature.

9) Transformation: a variable transformation $\boldsymbol{y}=\boldsymbol{x}^{0.5}$ is applied on each element of the extracted feature vector to make its distribution more Gaussian-like.

3.3 Classification

Linear discriminant analysis (LDA) and modified quadratic discriminant function (MQDF) are widely applied in character recognition due to their excellent performance [14][15]. In this paper, the LDA classifier and compact MQDF [16] classifier are employed.

For LDA classifier, we first extract the 8-directional feature, and then the extracted feature is projected to the LDA feature space and the dimension of the feature is reduced to 256 by implementing LDA algorithm. Finally, the minimum Euclidean distance classifier is employed to classify. For the compact MQDF classifier, the LDA classifier is employed for coarse classification, and the first ten candidates are fed into the compact MQDF classifier to output the final result.

4. Experiments

4.1 Experimental data

The benchmark dataset used in this paper come from the SCUT-COUCH database. It is a revision of SCUT-COUCH2008 [17], which is now contributed by more than 168 participants. All characters are written in an unconstrained manner. This database is a comprehensive dataset composed of 8 subsets: GB1 (level 1 GB2312-80) simple Chinese character, GB2 (level 2 GB2312-80) simple Chinese character, traditional Chinese character, word, Pinyin, digit, alphabet and symbol. (The SCUT-COUCH database is available at: http://www.hcii-lab.net/data/SCUTCOUCH/).

In this paper, a subset of SCUT-COUCH dataset, WORD8888, is adopted, which contains 128 writers' sample of **8,888** categories of word data(Total 128× 8888 handwriting word samples). For each category, we randomly selected 100(or 78.13 %) samples for training and remaining 28(or 21.87%) samples for testing. A part of experimental handwritten word samples is illustrated in Figure3.

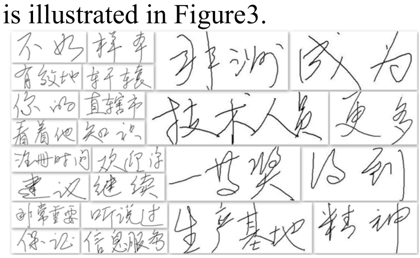

Figure3. **A part of experimental samples.**

4.2 Performance comparison of elastic meshing with nonlinear shape normalization

The first experiment is designed to compare the performance of elastic meshing (ELM) technique and the nonlinear shape normalization (NSN) technique. Since all of the testing words are non-rotated, the rotation correction algorithm is not employed in this experiment. The result is presented in Table2.

Table2. **Performance comparison of elastic mesh with NSN**

	LDA classifier	MQDF classifier
ELM	**93.38%**	**97.60%**
NSN	86.64%	93.52%

From Table2, it is observed that the ELM technique significantly outperforms the NSN technique. And the proposed holistic recognition method can achieve about 97.60% recognition accuracy for non-rotated word data.

4.3 Performance evaluation on rotated data

To demonstrate the efficiency of rotation correction method, we compare the performance of non-rotation correction method with the rotation correction method. The results are shown in Table 3. (In this table, "**With**" and "**Without**" stand for with and without rotation correction respectively).

From the Table3, it is found that when the rotation angle exceeds the range from -15° to +15°, the recognition accuracy decreases dramatically if the rotation correction is not implemented, and the rotation correction method can achieve an excellent performance on the rotated word data.

4.4 Performance comparison of the proposed method with analytic approach

T. LONG, LW. JIN [5] proposed a rotation free online unconstrained cursive handwritten Chinese word recognition method, where the rotation correction method is the same with ours, through an analytic approach (segmentation based method). By random rotation of all of testing data in range from 0º to 360º, the performance comparison of the proposed method with above analytic word recognition method is demonstrated in Table4. All the experiments were based on the same randomized rotation angle sequence.

Table3. **Performance comparison of with and without rotation correction**

Rotated angle		30º	20º	15º	10º	5º	0º	-5º	-10º	-15º	-20º	-30º
Without	LDA (%)	0.88	14.61	44.38	77.44	91.05	93.38	88.28	73.38	43.91	16.11	0.91
	MQDF(%)	1.34	24.97	65.61	93.32	98.40	97.60	97.62	91.69	70.00	33.86	2.32
With	LDA (%)	89.30	89.57	89.80	90.01	90.09	90.42	90.19	90.14	90.03	89.87	89.48
	MQDF(%)	96.31	96.63	96.79	96.90	96.98	97.06	97.05	97.00	96.92	96.79	96.45

Table4. **Performance comparison of holistic approach and analytic approach on randomly rotated word data**

Approach	MQDF (%)
Previous Analytic method [5]	84.87
Proposed holistic method	**96.58**

From the results in Table4, we can see clearly that the recognition accuracy of the proposed holistic method significantly outperforms that of the analytic approach, with the increase of recognition rate by 11.71%. It should be noted that the holistic methods usually have the limited and static lexicon. Thus, our proposed method can provide an excellent performance on small or medium static lexicon based handwritten Chinese word recognition.

5. Conclusion

In this paper, we proposed a rotation free method for online unconstrained cursive handwritten Chinese word recognition through a holistic approach. By implementing a novel gravity center balancing method, the rotation ranging from 0° to 360° of handwritten words can be detected. Then feature extraction based on elastic meshing technique is implemented to extract the 8-directional feature, which is fed into the classifier to output the final result. Experiments were performed on 8888 categories of 1,137,664 unconstrained handwritten Chinese word samples collected with Pocket PC. From the experimental results, we can conclude that: (1) The elastic meshing technique significantly outperforms the nonlinear shape normalization technique in online holistic word recognition; (2) The tolerant rotation range of the Chinese word is only within ±15°, and our proposed rotation free holistic word recognition method can achieve about 97±1% recognition accuracy on rotated word data; (3) Comparing with analytic approach, the proposed method can provide a much better recognition performance but its lexicon is limited and static; (4) The proposed method is suitable for the small or medium static lexicon based word recognition.

As described above, the holistic approach can provide an excellent performance on small or medium static lexicon based word recognition while the analytic approach has been successfully applied on large vocabulary word recognition [5]. A hybrid approach for HWR, which combines the holistic and analytic approaches, will be studied in the future research.

6. Reference

[1] C.-L. Liu, S. Jaeger, M. Nakagawa, "Online recognition of Chinese characters: the state-of-the-art", *IEEE Trans. on PAMI, Vol. 26, No. 2*, 2004, pp: 198 – 213

[2]Namboodiri, A.M. and Jain, A.K., "Online Handwritten Script Recognition", *IEEE Trans. on PAMI, Vol. 26, No. 1*, 2004, pp. 124-130

[3] Vinciarelli, A., "A survey on off-line Cursive Word Recognition", *Pattern Recognition, Vol. 35, No. 7*, 2002, pp. 1433-1446

[4] G. Kim, V. Govindaraju, "A lexicon driven approach to handwritten word recognition for real-time applications", *IEEE Trans. on PAMI, Vol. 19, No. 4*, 1997, pp. 366-379.

[5] Teng LONG, Lianwen JIN, "A Novel Orientation Free Method for Online Unconstrained Cursive Handwritten Chinese Word Recognition", *ICPR2008*, 2008

[6] Madhvanath, S. and Govindaraju, V., "The Role of Holistic Paradigms in Handwritten Word Recognition", *IEEE Trans. on PAMI, Vol. 23, No. 2*, 2001, pp. 149-164

[7] Ruiz-Pinales, J. , Jaime-Rivas etc., "Holistic cursive word recognition based on perceptual features", *Pattern Recognition Letters, Vol. 28, No. 13*, 2007, pp. 1600-1609

[8] Kim, J.H. and Kim, K.K. and Suen, C.Y., "An HMM-MLP Hybrid Model for Cursive Script Recognition", *Pattern Analysis and Application, Vol. 3, No. 4*, 2000, pp. 314-324

[9] Dehghan, M. and Faez, K etc., "Handwritten Farsi (Arabic) word recognition: a holistic approach using discrete HMM", *Pattern Recognition, Vol. 34, No. 5*, 2001, pp. 1057-1065

[10] Lee, L.L. and Coelho, SI, "A simple and efficient method for global handwritten word recognition applied to Brazilian bankchecks", *ICDAR2005*, pp. 950-954

[11] CL Liu, "Handwritten Chinese Character Recognition: Effects of Shape Normalization and Feature Extraction", *Lecture Notes in Computer Science, Vol. 4768*, 2008, pp.104-127

[12] LW. Jin, G. Wei, "Handwritten Chinese Character Recognition with Directional Decomposition Cellular Features", *Journal of Circuit, System and Computer*, 1998, 8(4), pp. 517-524.

[13] Zhen-Long, BAI and Qiang, HUO, "A Study On the Use of 8-Directional Features For Online Handwritten Chinese Character Recognition", *ICDAR2005*, 2005, pp. 232-236

[14] Duda, R.O. and Hart, P.E. and Stork, D.G. : *Pattern Classification*, Wiley New York, New York, 2001.

[15] S.N. Srihari, X. Yang and G.R. Ball, "Offline Chinese handwriting recognition: an assessment of current technology", *Frontiers of Computer Science in China, Vol. 3, No. 4*, 2007, 137-155.

[16] T. Long and L.-W. Jin, "Building Compact MQDF Classifier for Large Character Set Recognition by Subspace Distribution Sharing", *Pattern Recognition, Vol. 41, No. 9*, pp. 909-913, 2007.

[17] Yunyang Li, Lianwen Jin, Xinghua Zhu, Teng Long, "SCUT-COUCH2008: A Comprehensive Online Unconstrained Chinese Handwriting Dataset", *ICFHR2008*, 2008, pp. 165-170