2009 10th International Conference on Document Analysis and Recognition

An Investigation of Imaginary Stroke Technique for Cursive Online Handwriting Chinese Character Recognition*

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

Abstract

Imaginary stroke technique has been proved to be an effective solution to the problem of the stroke connection in online handwritten character recognition. However, it may cause confusions among characters with similar but actually different trajectories after adding imaginary strokes. In this paper, we first investigate both the benefit and the defect of the imaginary stroke technique, and then two modified methods are proposed under the framework of feature fusion and local feature enhance respectively. With the proposed methods, the feature of imaginary strokes is employed to unify the writing styles and the feature of real strokes is enhanced to strengthen discriminability. Experimental results for handwritten Chinese character recognition indicate that comparing with feature without imaginary strokes and feature with imaginary strokes, our proposed methods provide about 3%~8% and 1%~4% recognition accuracy improvement respectively.

1. Introduction

In recent years, new types of pen input devices and interfaces have been developed to improve the precision of trajectory capturing and the comfort of writing. It motivates the development of Online Handwriting Character Recognition (OLHCR) technology [1][2]. Owing to the availability of both temporal stroke information and spatial shape information, online character recognition is able to yield higher accuracy than offline recognition.

However, stroke connection, which is a universal phenomenon in OLHCR, may cause great shape distortion and seriously affect the recognition performance. To solve this problem, M.Okamoto etc [3][4][5] propose an imaginary stroke technique. In this technique, all of the characters are treated as one-stroke style characters by connecting all successive real strokes, and the trajectories between connected successive real strokes are considered as imaginary strokes.

However, by treating imaginary strokes as real strokes, some similar but different characters are confused. As shown in Figure1, the trajectories between character '氵(water)' and '讠(talk)', '亏(deficit)' and '弓(bow)', and '云(cloud)' and '六(six)' become indistinguishable even for humans.

Fig1. **Discrimination reduction with imaginary strokes**

To overcome above problems, we investigate both the benefit and the defect of the imaginary strokes through analysis and experiments for the first time. And then two modified methods are proposed under the framework of feature fusion and local feature enhance respectively. By combining the advantages of imaginary strokes and real strokes, our proposed methods not only unify the various writing styles, but also decrease the unfavorable effect of imaginary strokes. The experimental results demonstrate that the proposed methods provide significant improvement to the recognition performance.

The rest of this paper is organized as follows. Imaginary stroke technique and its characteristics are presented in section 2; and then the details of the introduced methods and experiments are given in Section 3 and Section 4 respectively. Finally, the conclusions are summarized in Section 5.

* 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.2009.29

2. Imaginary stroke

In practical, stroke connection is widely adopted by humans to accelerate the writing speed. However, this tendency will lead to great shape distortion compare with neatly written characters. To recognize cursive characters with connected strokes and neatly written characters without increasing standard character patterns, the imaginary stroke technique was proposed by M.Okamoto et at [3][4][5] and has been proved to be very effective for OLHCR[3][4][5][6].

In general, the imaginary stroke technique simulates the human's stroke connection habit and unifies the writing styles to certain degree; therefore, it can provide a better performance than not adding imaginary strokes.

Nevertheless, due to the original character patterns are disturbed by imaginary strokes, some similar but actually different characters become indistinguishable even by humans (as shown in Figure 1). On the other hand, the one-stroke writing style is also inconsistent with real situation, for few of the characters are written as one-stroke-style characters in practical for most of people. Moreover, considering the large vocabulary of Chinese characters, it may be expected that there are a large number of similar characters could be fussed by imaginary strokes.

To study the characteristic of imaginary stroke technique, experiments are designed to evaluate the performance of imaginary stroke technique in section 4.2. It is found that, by adding imaginary strokes, the performance of a lot of characters decreased greatly, although the overall performance improved.

3. Proposed methods

3.1 Elastic mesh based 8-directional feature

The feature we used in this paper is the 8-directional feature proposed by ZL Bai and Q. Huo[6]. And we replace the nonlinear shape normalization (NSN) with a better performance elastic meshing technique [7]. The method is described as follows:

1) Linear normalization: the original character trajectories are normalized to a fixed size of 64×64 using an aspect-ratio preserving linear mapping
2) Adding imaginary strokes: the imaginary stroke technique is implemented in this step.
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, its direction vector $\vec{V_j}$ is defined as follows:

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

6) Projection: the directional vector is projected to 8 directional axes to generate an 8-dimensional direction code at each trajectory point.
7) Blurred: we divide the character image into 8×8 sub-blocks using elastic meshing technique[7]. Within each sub-block, the 8-dimensional direction codes are blurred by a Gaussian filter, resulting in a 512-dimensional feature.
8) 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.

In the following sections, we call the 8-directional feature as **imaginary stroke 8-directional feature** if the second step is employed; otherwise, as **non-imaginary stroke 8-directional feature**.

3.2 Fusion of imaginary stroke feature and non-imaginary stroke feature

In recent years, feature fusion has been developed rapidly and widely applied in many areas especially in pattern classification field [8][9]. By optimizing and combining different features, feature fusion technique not only preserves the effective discriminant information of multi-feature, but also avoids their disadvantages to certain degree. On the other hand, linear discriminant analysis (LDA) is well known in pattern classification area since it can project the original feature space to a new feature space that best discriminate among classes.

In this paper, we intend to introduce a feature transformation based feature fusion framework to combine the imaginary stroke feature and non-imaginary stroke feature in the LDA transformed feature space.

Let X and Y are two different features, which stand for imaginary stroke feature and non-imaginary stroke feature respectively in this paper, in feature space $\boldsymbol{\Phi}$ and $\boldsymbol{\Psi}$ respectively, and W is the fusional transformation matrix. In general, the fusional feature Z, which feature space is $\boldsymbol{\Omega}$, can be obtained through the formulation (2):

$$Z = W \left(X \quad Y \right)^T \quad (2)$$

In our approach, we design the following two linear transformations shown in eq. (3) and (4):

$$Z_1 = W_1 (X\ Y)^T = (k_x W_x\ k_y W_y)(X\ Y)^T = k_x W_x X + k_y W_y Y \quad (3)$$

$$Z_2 = W_2 (X\ Y)^T = \begin{pmatrix} k_x W_x & 0 \\ 0 & k_y W_y \end{pmatrix} (X\ Y)^T = (k_x W_x X,\ k_y W_y Y) \quad (4)$$

where $W_1 = (k_x W_x\ k_y W_y)$, $W_2 = \begin{pmatrix} k_x W_x & 0 \\ 0 & k_y W_y \end{pmatrix}$; W_x and W_y are transformation matrixes in feature space $\boldsymbol{\Phi}$ and $\boldsymbol{\Psi}$ respectively; k_x and k_y are the weighting factors of W_x and W_y.

Through equation (3) and (4), we can obtain two new fused features Z_1 and Z_2, which are called as **parallel fusional 8-directional feature** and **serial fusional 8-directional feature** respectively.

According to formulation (3) and (4), these three situations are considered in this paper

(1) $W_x=W_y=I$, the fusional feature Z just the linear combination of X and Y.

(2) $W_x=W_{lda\_x}$ and $W_y=W_{lda\_y}$, the original feature X and Y are projected to their LDA feature space using W_{lda_x} and W_{lda_y} respectively and then combined to $\boldsymbol{Z}$

(3) $W_x= W_y =W_{lda\_z}$, the original feature X and Y are fused first, and then project to the LDA feature space using W_{lda_z}.

Here, W_{lda_x}, W_{lda_y} and W_{lda_z} are the LDA projection matrixes in feature spaces $\boldsymbol{\Phi}$, $\boldsymbol{\Psi}$ and $\boldsymbol{\Omega}$ respectively.

3.3 Local enhance 8 directional feature

Generally, the global topology of Chinese character is preserved by the real strokes, and the imaginary strokes are just the assistances to integrate various writing styles. Due to this characteristic, various characters can be recognized by humans though their shape may be distorted by various writing styles. That means the real strokes play the leading role in recognition and the imaginary strokes may just promote the performance to certain degree. According to this, a local enhance feature extraction is proposed to combine both the benefit of real strokes and imaginary strokes.

In reference [6], the imaginary strokes are treated as real strokes and then directional vectors of all sample points are extracted without distinguishing the real stroke and imaginary stroke. Yet in our proposed method, the directional vectors of real strokes are strengthened by multiplying a weight factor k (in our experiments, we set $k=5$). The detail is described as follows:

Considering the fifth steps of 8-directional feature extract method described in section 3.1. The directional vector $\vec{V_j}$ would be strengthened to $k\vec{V_j}$, if the point P_j is located in real stroke.

4. Experiments and Results

4.1 Experimental data

The benchmark data used in this paper come from the SCUT-COUCH database. It is a revision of SCUT-COUCH2008 [12], 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 two subsets of SCUT-COUCH dataset are adopted, which contain 168 writers' samples of **6763** categories of GB1 and GB2 subsets (Total 168× 6763 handwriting samples). For each character category, we randomly selected 134(or 79.16%) sets of samples for training and remaining 34(or 20.84%) sets of samples for testing. And both the original feature and LDA feature are employed to evaluate the performance on testing dataset through a minimum Euclidean distance classifier.

4.2 Investigations of the impact of imaginary stroke technique for recognition performance

The first experiment is designed to evaluate the performance of the imaginary stroke technique by comparing with non-imaginary stroke feature, the character recognition accuracies are summarized in Table1 (In this table, "**Org**" stands for original feature, "**LDA**" for LDA feature, "**D**" for dimension, "**Imaginary**" and "**Non-imaginary**" for imaginary and non-imaginary stroke 8-direcitonal feature respectively).

Table1. **Performance comparison of imaginary stroke feature with non-imaginary stroke feature**

Method		Accuracy
Org (D=512)	Non-imaginary	82.66%
	Imaginary	**87.16%**
LDA (D=96)	Non-imaginary	87.78%
	Imaginary	**89.95%**

From Table1, we can clearly see that, by adding imaginary strokes, the accuracy performance is significantly improved, the same conclusion was observed in reference [6].

Besides investigate the overall accuracy performance of the imaginary stroke feature, another experiment is designed to evaluate the proportion of recognition accuracy changes after adding imaginary strokes.

Assume the total category number is N. Let N_1, N_2 and N_3 be the number of categories in which the accuracy recognition is increased, remain unchanged or decreased respectively. Then we define the Increase ratio (***IncR***), Same ration (***SameR***) and Decreased ration (***DecR***) as follows:

$$IncR = {N_1}/{N} \times 100\% \quad (5)$$

$$SameR = {N_2}/{N} \times 100\% \quad (6)$$

$$DecR = {N_3}/{N} \times 100\% \quad (7)$$

Table2. **Proportion of recognition accuracy changes with imaginary strokes**

	Org (D=512)	LDA (D=96)
IncR	64.08%	58.72%
SameR	14.51%	19.40%
DecR	21.41%	21.88%

As shown in Table2, it is observed that, by adding the imaginary strokes, the accuracy performance of above 58% of total 6763 categories increases while above 21% decreases. Since *IncR>>DecR*, imaginary stroke feature provides improvement of accuracy performance. However, a number of characters become hard to recognize after adding imaginary strokes. Some typical examples are given in Table 3.

Table3. **Examples of characters whose accuracy decreased greatly after adding imaginary strokes**

	Org (D=512)		LDA(D=96)	
	Non-imaginary	Imaginary	Non-imaginary	Imaginary
入	79.41%	73.53%	91.18%	70.59%
溪	85.29%	64.71%	91.18%	67.65%
鬓	82.35%	64.71%	85.29%	67.65%
卸	88.24%	82.35%	91.18%	76.47%
伊	73.53%	70.59%	94.12%	79.41%

From these experiments, it is observed that: (1) Adding imaginary strokes provides a better overall performance than not adding imaginary strokes; (2) The recognition accuracies of some characters are greatly decreased due to the confusions caused by imaginary strokes.

4.3 Parameters determination for fusional feature

In this section, we'll determine the optimal fusional matrixes and weighting ratios for equation (3) and (4) through experiments.

Table 4 shows a comparison result of different fusional matrixes, which are described in section 3.2.

Table4. **Determination of fusional matrixes**

Method			Accuracy
Parallel fusional feature	D=96	$W_x=W_{lda\_x}$, $W_y=W_{lda\_y}$	87.25%
		$W_x=W_y=W_{lda\_z}$	91.14%
	D=512	$W_x=W_y=I$	88.68%
Serial fusional feature	D=96	$W_x=W_{lda\_x}$, $W_y=W_{lda\_y}$	91.17%
		$W_x=W_y=W_{lda\_z}$	**92.43%**
	D=1024	$W_x=W_y=I$	90.89%

As it is shown in Table4, when $W_x=W_y=W_{lda\_z}$, the performance is the best for both parallel fusional feature model and serial fusional model.

By defining the fusional matrixes as $W_x=W_y=W_{lda\_z}$, the other set of experiments are performed to compare various weighting ratios. The results are given in table 5, it can be seen that when k_x:k_y=*1:1,* the performance is best.

Table5. **Comparison against various weight ratios**

$k_x : k_y$	Parallel fusional feature		Serial fusional feature	
	Org	LDA	Org	LDA
1:5	85.40%	89.19%	84.26%	92.38%
1:4	85.91%	89.51%	85.02%	92.38%
1:3	86.59%	89.89%	86.40%	92.38%
1:2	87.55%	90.50%	88.60%	92.40%
1:1	88.68%	**91.14%**	**90.89%**	**92.43%**
2:1	**88.76%**	91.06%	89.61%	92.42%
3:1	88.52%	90.85%	88.53%	92.41%
4:1	88.31%	90.65%	88.01%	92.41%
5:1	88.12%	90.52%	87.75%	92.40%

4.4 Performance comparison of proposed features against imaginary stroke and non-imaginary stroke 8-direcitonal feature

In this section, we try to compare the comprehensive performance of the proposed three new features against original imaginary stroke and non-imaginary stroke 8-directional features.

Ⅰ. Accuracy and time consumption performances comparison:

The accuracy and time consumption performances of various features are shown in Table6 and the testing platform is on a PC with Core2 Duo 2.20G CPU and 1G Memory. (In this table, "**Parallel**", "**Serial**" and "**Local**" for parallel fusional, serial fusional and local enhance 8-directional feature respectively)

Table6. **Performance comparison of accuracy and time consumption**

Feature	Org	LDA	Time (μs/char)
Non-imaginary	82.66%	87.78%	649
Imaginary	87.16%	89.95%	720
Parallel	88.67%	91.14%	1372
Serial	90.89%	92.43%	1371
Local	89.41%	**91.45%**	**725**

From the result shown in Table6, it is indicated that the accuracy performance of the proposed methods outperforms the traditional two features. The time consumption of parallel and serial fusional feature is about twice of non-imaginary stroke feature and imaginary stroke feature. However, comparing with non-imaginary stroke feature and imaginary stroke feature, the accuracy of proposed local enhance feature is increased 4%~7% and 1.5%~2.3% respectively while the time consumption is only increased 11.71% and 0.69% respectively.

Ⅱ Proportion of recognition accuracy changes of the proposed features and imaginary stroke feature

Comparing with the non-imaginary stroke feature, the proportion of recognition accuracy changes of various features are given in Table7.

Table7. **Proportion of recognition accuracy changes of various features**

Feature		*IncR*	*SameR*	*DecR*
With	Org	64.08%	14.51%	21.41%
	LDA	58.72%	19.40%	21.88%
Parallel	Org	74.79%	15.95%	9.26%
	LDA	61.89%	22.82%	15.29%
Serial	Org	**85.39%**	10.47%	**4.14%**
	LDA	69.10%	18.73%	12.17%
Local	Org	77.60%	13.85%	8.55%
	LDA	63.54%	20.45%	16.01%

From the Table7, it is observed that comparing with imaginary stroke feature; our proposed three features significantly decrease the unfavorable effect of imaginary strokes.

5. Conclusions

In this paper, we have investigated both the benefit and the defect of imaginary stroke technique. We found that by adding imaginary strokes, although the overall performance significantly improved, a number of characters' performance decreased greatly at the same time. To solve this problem two modified methods are proposed under the framework of feature fusion and local feature enhance. The experimental results demonstrated that, our proposed methods give a better accuracy performance than both imaginary stroke feature and non-imaginary stroke feature. Considering the accuracy and time consumption, the proposed local enhance feature may be a good choice to achieve best trade-off performance.

6. References

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

[2] Tappert CC, Suen CY, Wakahara T, "The State of the Art in Online Handwriting Recognition", *IEEE Transactions on PAMI, Vol. 12, No. 8*, 1990, pp. 787-808

[3] M. Okamoto, A. Nakamura, and K. Yamamoto, "On-line Handwriting Character Recognition Method with Directional Features and Directional Change Features", *ICDAR 1997*, 1997, pp.926-930.

[4] M. Okamoto, A. Nakamura, and K. Yamamoto, "Direction-change features of imaginary strokes for on-line handwriting character recognition," *ICPR1998*, 1998, pp. 1747-1751

[5] M. Okamoto and K. Yamamoto, "On-line Handwriting Character Recognition Using Direction change Features That Consider Imaginary Strokes", *Pattern Recognition, Vol.32, No. 7*, 1999, pp.1115-1128.

[6] 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

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

[8] H.-C. Chiang, R.L. Moses, L.C. Potter, "Model-based Bayesian feature matching with application to synthetic aperture radar target recognition" *Pattern Recognition*, *Vol.34, No. 8*, 2001, pp. 1539－1553

[9] Yang, J. and Yang, J. and Zhang, D. and Lu, J., "Feature fusion: parallel strategy vs. serial strategy", *Pattern Recognition*, *Vol.36, No. 6*, 2003, pp. 1369—1381.

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