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A Novel Approach for Rotation Free Online Handwritten Chinese Character Recognition+

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Abstract

This paper presents a method for rotation free online handwritten Chinese character recognition (RFOHCCR). Given a skew online handwritten character sample, two orientation correction steps, including angle rectification according to the starting point, angle readjustment based on principal direction axes, are first performed to rectify the skew angle of the sample. Then 8-directional feature is extracted and the character is classified using the classifier trained by artificially rotated samples. Experiments on 863 online Chinese character dataset and SCUT-COUCH dataset show the effectiveness of the proposed approach.

1. Introduction

In this paper, we study the problem of how to recognize the rotated online Chinese character. Although previous work on normal online handwritten Chinese character recognition (OHCCR) [1,4,7] has shown promising results, it is not rotation invariant. Although effective methods for rotation free word recognition[3,5] have been proposed, they are not suitable for rotation free character recognition. Until now, Research on rotation free isolated online handwritten Chinese character recognition(RFOHCCR) does not come out with a promising result, and it remains a tough problem to be solved. The primary motivations of this study are to find some solutions and clues for the problem of RFOHCCR.

For OHCCR, 8-directional feature has been shown effective [1]. However, as for skew Chinese character, the 8-directional feature extracted is much different from the one for the normal character. Therefore, 8-directional feature can't be applied directly on RFOHCCR. In this paper, we propose several novel techniques to make 8-directional feature perform well also in RFOHCCR. Various experiments are conducted to show the effectiveness of our methods.

The rest of the paper is organized as follows. Details of several techniques for RFOHCCR are described in Section 2. Experimental results of our approach are reported in Section 3. Finally, conclusions are summarized in Section 4.

2. Our Approach

The overall flowchart of our RFOHCCR approach is shown in Fig.1. In the following subsections, we explain in detail how each module works.

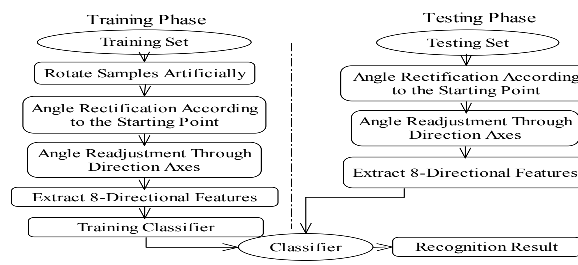

Figure 1. **Overall Flowchart of RFOHCCR.**

2.1 Skew angle rectification according to the starting point(SAR-SP)

The main objective of this step is to insure that the Chinese character is not over-rotated. If the Chinese character is rotated by an angle larger than 180 degree, some of Chinese characters seem to be the same, such as the Chinese characters "土" and "干", which make them rather difficult to be separated. By using the time sequence information of the online Chinese character, we find a way to roughly rectify a rotated character.

The method is based on the observation that for Chinese characters, the starting points of most of them always locate in left, top, or upper left of the character, as shown in Figure 2. Inspired by this, we utilize the

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starting point of an online handwritten character for rectification.

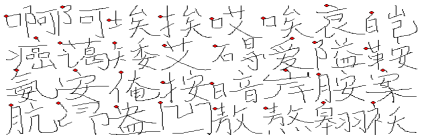


Figure 2. **Starting points (red filled circles) of some Chinese characters.**

First, To search the location of the starting point, we divide the online handwritten Chinese character into four segments as shown in Figure 3.

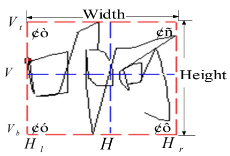


Figure 3.**Dividing character into 4 segments**

The horizontal and vertical segmentation line V and H satisfy the following constraints:

$$\int_{1}^{Height}\int_{H_l}^{H} f(x,y)dxdy = \int_{1}^{Height}\int_{H}^{H_r} f(x,y)dxdy \qquad (1)$$

$$\int_{V_b}^{V}\int_{1}^{Width} f(x,y)dxdy = \int_{V}^{V_t}\int_{1}^{Width} f(x,y)dxdy$$

Where H_l, H_r, V_b, V_t denote the boundaries of image, and $f(x,y)$ of each pixel is defined as:

$$f(x,y)=\begin{cases}1 & \text{if pixel(xy) is a sampling point}\\ 0 & \text{if pixel(xy) is not a sampling point}\end{cases} \qquad (2)$$

As shown in Fig.4, the horizontal and the vertical dash segmentation lines divide the character into four parts. Then We assume the intersection point of the two dash lines as origin, and rectify the phase angle of its starting point θ to $\theta \bmod 90^o + 90^o$ to insure its starting points locates in upper left segments, Accordingly, character image is rotated according to formula (3). Fig. 4 shows some examples of skew angle rectification.

$$x_i' = x_i * \cos((1-\lfloor\theta/90^o\rfloor)*90^o) + y_i * \sin((1-\lfloor\theta/90^o\rfloor)*90^o) \qquad (3)$$
$$y_i' = y_i * \cos((1-\lfloor\theta/90^o\rfloor)*90^o) - x_i * \sin((1-\lfloor\theta/90^o\rfloor)*90^o)$$

Let's denote the phase angle of starting point of a normal character as θ', and assume the character is rotated by θ'', the difference between the rectified angles of both θ' and $\theta'+\theta''$ is given by:

$$\|\theta_{diff}\| = \|(\theta'+\theta'') \bmod 90 + 90 - (\theta' \bmod 90 + 90)\|$$
$$= \|(\theta'+\theta'') \bmod 90 - (\theta' \bmod 90)\| \le 90 \qquad (4)$$

This indicates that after rectification of both normal and skew sample, the difference between their rotation angles is not larger than 90 degree. And characters like "土" and "干" are distinguishable after such rectification even they were written the same due to rotation.

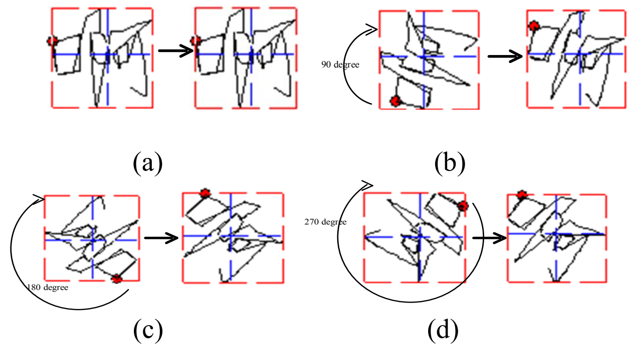


Figure 4. **Different Rotated character and rectification according to starting points(red filled circles), Rotated angle:(a) 0 degree;(b) 70 degree;(c) 130 degree;(d) 230 degree.**

For the characters of which the starting points do not locate in the upper left, we also rotate them back to insure their starting points locate in upper left part uniformly.

In order to confirm the assumption that starting points of most of online handwritten Chinese characters always locate in left, top, or upper left of the character, we make a statistics using the online handwritten character dataset provided by the 863 project in China. Experiments indicate that the starting points of most of the Chinese characters locate in the upper left part or around, $45^o \le \theta' \le 225^o$. An example of the distributions of the starting points of four characters from 60 handwritten samples is shown in Fig.5. Compared with normal sample, a skew sample rotates with an angle θ'_{diff} after rectification, which is given by:

$$\|\theta'_{diff}\| = \|(\theta'+\theta'') \bmod 90^o + 90^o - \theta'\| \qquad (5)$$
$$\le 135^o, \quad 45^o \le \theta' \le 225^o$$

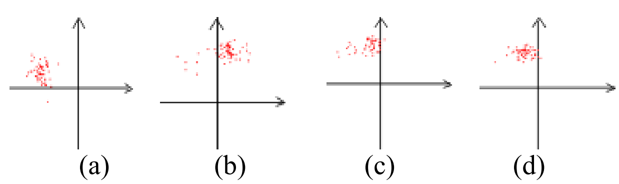


Figure 5. **distributions of starting points of some handwritten Chinese characters:(a) character "啊";(b) character "爱"; (c) character "崔"; (d) character "磐".**

Especially for those of which starting points locate in upper left, we have:

$\theta' \in [90^o, 180^o], \|\theta'_{diff}\| <= 90^o$

The above shows that such angle rectification is reasonable and effective to avoid character from over-rotated.

2.2 Angle readjustment using direction axes(AR-DA)

After rectify the character through starting point, we readjust the skew angle through principal direction axes. The motivation is to rotate the character sample to several uniform direction axes. Inspired by the 4-directional feature[2], where four directions are defined naturally as vertical(|), horizontal(-), left-up(/) and right down(\), our basic idea is to project a direction vector onto four direction axes to rectify the rotated angle, the direction vector $\overrightarrow{V_j}$ is defined as follows[1]:

$$\overrightarrow{V_j} = \begin{cases} \overrightarrow{P_j P_{j+1}} & \text{if } P_j \text{ is a start point} \\ \overrightarrow{P_{j-1} P_{j+1}} & \text{if } \mathrm{P_j} \text{ is a non}-\text{end point} \\ \overrightarrow{P_{j-1} P_j} & \text{if } \mathrm{P_j} \text{ is an end point} \end{cases} \qquad (6)$$

As shown in Fig.6, each direction vector $\overrightarrow{V_j}$ can be projected to two of the four direction axes.

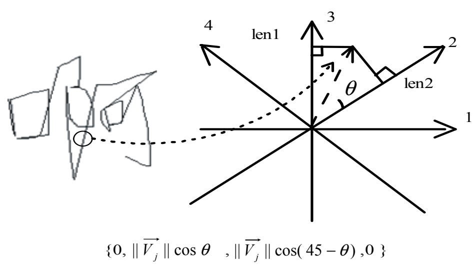


Figure 6. **Projecting a direction vector onto four direction axes and the direction vector's projection lengths on four direction axes.**

Let $\overrightarrow{SL} = \{SL_1, SL_2, SL_3, SL_4\}$ denote the projection lengths vector on four axes, $\overrightarrow{L^j} = \{L^j{}_1, L_2{}^j, L_3{}^j, L_4{}^j\}$ be the projection lengths vector of each $\overrightarrow{V_j}$, then we have $\overrightarrow{SL} = \sum_j \overrightarrow{L^j}$.

We set the ith direction as the principal direction $\overrightarrow{D_p}$, $i = \arg\max_n \{SL_n\}, n = 1,2,3,4$. Then a virtual direction $\overrightarrow{D_v}$ is computed as follows:

$$\overrightarrow{D_v} = \sum_{j \in S} \frac{L^j{}_i}{SL_i} \theta_j \qquad (7)$$

Where S is the set of direction vectors of which L_i are not zero, θ_j is the angle of the jth direction vector relative to the principal direction. If θ_j>180, θ_j = θ_j - 180. If i = 1 and θ_j>135, θ_j=180-θ_j.

After determining principal and virtual direction, we rotate the character by angle between them. As shown in Fig. 7, the characters on the left are the skew characters after rectification according to the starting points, the characters on the right are the characters after angle readjustment. Dash line in blue indicates the virtual direction, and dash line in red indicates the principal direction. Linear normalization is performed after angle readjustment. Figure.7 shows that angle readjustment helps rotate the skew character to four direction axes or near. In a word, Angle readjustment reduces the angle variation and contributes to the recognition afterwards as we will see in experiment in Section 3.5.

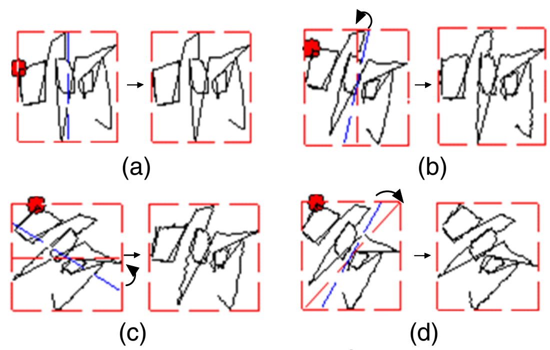


Figure 7. **Readjustment of Chinese character sample rotated by: (a) 0 degree (the dash line in red is covered by the dash line in blue);(b) 70 degree;(c) 130 degree;(d) 230 degree.**

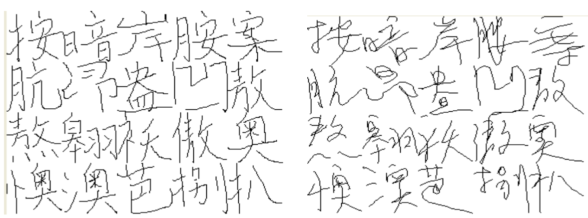
2.3 Training classifier using artificially rotated samples(TC-ARS)

It should be notable that the handwritten samples from many datasets are non-rotated samples. Therefore, if we only extract the 8-directional features of the normal Chinese character samples to train the classifier, the recognition accuracy is not good enough, as it will be seen later in experiments in Section 3.2. Therefore, we use artificially rotated samples of each character to train the classifier. The motivation behind this is to adapt the classifier to the rotated character samples. However, how many times should we rotate a normal sample to extract features, and how to determine the rotated angle each time remain problems. Let N be times of rotating samples artificially and A be the set of angles rotated each time in degree. In Section 3.2, experiments are carried out to find the suitable parameters N and A.

3. Experiments and results

3.1 Experimental setup

To evaluate the efficacy of our proposed techniques, a series of experiments are conducted on two online handwritten Chinese character datasets, 863 online Chinese character dataset and SCUT-COUCH dataset from HCII lab of SCUT[8](The dataset has been updated from 50 writers to 168 writers now). As for 863 dataset, it contains 60 writers' samples, where 45 writers' samples are selected randomly as the training set, and the rest 15 writers' samples as the testing set. As for SCUT-COUCH dataset, it includes 168 writers' samples, among them, 132 writers' samples are chosen randomly to form the training set, while the rest 36 writers' samples form the testing set. Samples of 20 characters from 863 dataset are shown in Fig.8 (a), and samples of the same characters from SCUT-COUCH dataset are shown in Fig.8 (b). It can be seen that samples from 863 dataset are more regular, while samples from SCUT-COUCH are more cursive like. In our experiments, minimum distance classifiers before and after LDA (Linear Discriminant Analysis) are used. The total categories of character we used are 500 and 3755 level 1 GB2312-80 standard respectively. If not stated specifically, samples from testing set are rotated randomly before classification.



(a) (b)

Figure 8.**Samples of 20 characters from dataset: (a)863 dataset; (b)SCUT-COUCH dataset.**

3.2 A comparison of training classifier using artificially rotated samples

This set of experiments is carried out to compare the performances of training classifiers using different N and A. As stated in Section 2.3, N is the times of rotating samples artificially and A is the set of angles rotated each time. Note that angle rectification and readjustment are conducted before extracting features. Recognition accuracies based on raw features and features after LDA are both given in Table 1. The dimension of raw feature is 512, and it is reduced to 96 after LDA. From Table 1, we can see that: 1) classifier trained through hybrid normal samples and artificially rotated samples performs much better than classifier trained only through normal samples; 2) Using LDA can greatly improve the recognizing capability; 3) larger N do not necessarily perform well; 4) N=3, A= {-45, 0, 45} are good options for our approach. Therefore, in later experiments, we always set N to 3, A to {-45, 0, 45}.

Table 1. **A comparison of training classifier using artificially rotated samples**

Dataset	863 dataset	
Category number	500	
Recognition Accuracy(in %)	Accuracy	Accuracy After LDA
N=1,A={0}	47.2	62.1
N=3,A={-45,0,45 }	57.4	**88.5**
N=3,A={0,45,90}	54.7	85.7
N=5,A={-90,-45,0,45,90}	56.4	87.4
N=8,A={-180,-135,-90, -45,0,45,90,135}	**58.0**	88.1

3.3 A comparison of using 8-directional feature directly vs. applying our approach

This set of experiments is designed to compare the performances of using 8-directional feature directly (extracting the features of normal samples to train the classifier, no angle rectification is applied to the rotated samples) with applying our proposed approach. We refer to them as without and with angle rectification. Recognition accuracies on 863 dataset and SCUT-COUCH dataset are shown in Table 2 and 3 respectively. From the results, it can be seen that: 1) Our approach is effective even for 3755 categories; 2) Our approach improves the recognition accuracies of both 863 and SCUT-COUCH dataset significantly. As for 863 dataset, the accuracy is improved greatly from 12.9% to 88.5% for 500 categories and 10.7% to 78.8% for 3755 categories.

Table 2. **A comparison of recognition accuracies of without and with angle rectification on 863 dataset.**

Dataset	863 dataset			
Method	Without angle rectification		With angle rectification	
Category number	500	3755	500	3755
Accuracy (%)	12.3	9.8	**57.4**	**43.8**
Accuracy after LDA(%)	12.9	10.7	**88.5**	**78.8**

Table 3. **A comparison of recognition accuracies of without and with angle rectification on SCUT-COUCH dataset.**

Dataset	SCUT-COUCH dataset			
Method	Without angle rectification		With angle rectification	
Category number	500	3755	500	3755
Accuracy (%)	11.2	8.3	**50.4**	**36.6**
Accuracy after LDA(%)	12.2	9.6	**79.9**	**65.9**

3.4 A comparison of recognition accuracies of characters with different rotated angles

This set of experiments is designed to compare the performances on characters rotated by different angles using our approach. We rotate all the character samples from testing dataset by an angle α before extracting features. For different α, the recognition accuracies of 500 categories are given in Table 4. It is observed from table 4 that our approach is stable and effective for different rotated angles, no matter it is applied to the characters all rotated by a fixed angle or rotated randomly.

Furthermore, an experiment on normal character samples of 3755 categories from testing set out of 863 dataset is also conducted. The recognition accuracy after LDA turns out to be 84.4%. It indicates that our approach does not have a greatly adverse impact on the recognition accuracy for normal characters while it is designed for RFOHCCR.

Table 4. **A comparison of recognition accuracies (in %) of character samples rotated by different angles.**

Dataset	863 dataset	
α (degree)	Accuracy	Accuracy after LDA
0	59.6	**92.5**
30	58.3	87.2
60	52.1	85.3
90	59.4	**92.2**
150	51.1	84.6
180	59.5	**93.1**
220	73.0	90.9
270	59.5	**92.8**
305	65.0	88.4
Random	57.4	88.5

3.5 A comparison of recognition accuracies using our approach partly

This set of experiments is conducted to confirm the effectiveness of every step of our approach. As explained in Section 2, our methods include the 3 steps of SAR-SP, AR-DA, TC-ARS. Applying our approach partly on samples of 3755 categories from 863 dataset, the curves of recognition accuracy of different steps are shown in Fig. 9. From figure 9, it can be seen that every step of our approach contributes to the improvement of the recognition accuracy, especially for accuracy after LDA. And we also observe that LDA is very useful in RFOHCCR.

4. Conclusion

In this paper, we have presented a study on how to solve the problem of rotation free OHCCR. A promising approach has been proposed after a careful study of online characters' time sequence and principal direction information. The proposed method includes three techniques of skew angle rectification according to the starting point, angle readjustment using direction axes, and training classifier using artificially rotated samples. All these novel techniques contribute to the improvement of the recognition accuracy as shown in experiments.

To summarize, our proposed approach shows its stability and effectiveness for RFOHCCR on both 863 dataset and SCUT-COUCH dataset. The encouraging experimental results indicate our method to be a potential success for RFOHCCR.

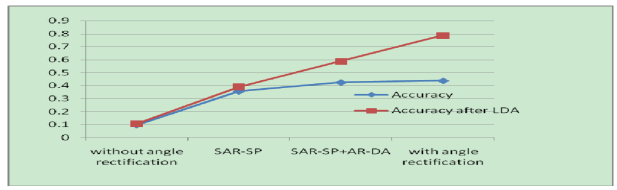


Figure 9. **Accuracy curve of applying our approach partly**

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