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A Character-Structure-Guided Approach to Estimating Possible Orientations of a Rotated Isolated Online Handwritten Chinese Character

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Abstract

This paper presents a character-structure-guided approach to estimating possible orientations of a rotated isolated online handwritten Chinese character. Using the estimated orientations, the original distorted sample can be transformed to a normal position, which can be recognized more accurately by using a classifier trained from normal-position samples. The effectiveness of this approach is demonstrated by recognizing rotated samples generated artificially from the popular Nakayosi and Kuchibue Japanese character databases, with average recognition accuracies of 96.05%, 97.35% and 99.13% on top-6, top-12, and top-100 candidates, respectively.

1 Introduction

As the use of portable digital assistants with pen-based input is increasing, online handwritten character recognition is becoming more important. At present, most online Chinese character recognition technologies assume the use of writing boxes for entering characters. Although writing boxes enable a high level of recognition accuracy to be maintained, they also impose an extra burden on the writers. It is obvious that if a distorted sample is fed into a conventional classifier trained from normal samples, poor recognition results will be expected. In order to make full use of the advantages offered by pen-based input, there is a great need for the development of writing-box-free online character recognition technology.

The techniques invariant to some specific distortions have been studied for handwritten characters in the literature. One type of the promising methods is to introduce an additional preprocessing step to transform the distorted characters to the normal positions [4, 6, 7]. Reasonable performances have been reported on the recognition of lines of characters [6, 7] or Chinese words [4], where informative clues for estimating the character orientations are provided. However these approaches are not so effective to isolated characters, since only little reliable information could be retrieved there.

In this paper, inspired by the works in [6, 7], we present a new character-structure-guided orientation estimation approach, designed specially for isolated online handwritten Chinese characters. It is our hope that by introducing this additional preprocessing step, the original distorted sample can be transformed to a normal position using the estimated orientations, which can then be recognized more accurately by using a classifier trained from normal-position samples. The effectiveness of this approach has been evaluated by recognizing rotated samples generated artificially from the popular Nakayosi and Kuchibue Japanese character databases.

The rest of the paper is organized as follows. In Section 2, we present our newly proposed character-structure-guided orientation estimation approach in detail. The experimental results are then reported in Section 3. Finally, we conclude this paper in Section 4.

2 Character-Structure-Guided Orientation Estimation Approach

Recently, compensating character orientations has been studied for lines of characters [6, 7]. By transforming the distorted sample to the normal position with rightward and downward principal axes, a possible character orientation could be assumed accordingly. Although reasonable performance has been achieved on some specific tasks, this approach is not effective to isolated online handwritten Chinese character since the assumed principal axes are not so reliable when the number of characters is limited. In the following, we present a new character-structure-guided orientation estimation approach designed specifically for isolated Chinese characters. Similar to the strategies in [6, 7], we estimate the orientations by monitoring the primary axes of the characters, represented as the modes of the directional histograms. To better understand our approach, in the following, we firstly illustrate the extraction of the directional feature and the construction of the directional histogram by using a similar approach as in [6, 7].

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2.1 Extraction of Directional Feature

Given a handwritten character sample, in the preprocessing step, firstly, the captured raw "ink" is smoothed and the whole character is normalized to an $N \times N$ ($N = 256$) online character sample using an aspect-ratio preserving linear mapping. Then, imaginary strokes, each connecting two consecutive real strokes, are added to form a new sample. After that, dominant points are detected, which include stroke-endings and points corresponding to local extrema of curvature. Each line segment between two dominant points are then resampled by using an equal-arc-length resampling procedure with a fixed sampling distance of 20. Consequently, each character sample is represented as a time-ordered sequence of points, $\mathbf{P} = (P_0, P_1, \cdots, P_t, \cdots, P_T)$, where $P_t = (x_t, y_t)$ is the coordinates of the t-th point. At each point, a simple directional feature is extracted as follows:

$$O_t = \begin{cases} \frac{\pi}{2} - \alpha & \text{if } \alpha \in [-\pi, \frac{\pi}{2}] \\ 2.5\pi - \alpha & \text{otherwise} \end{cases}$$

where $\alpha = \arctan(\frac{y_t - y_{t-1}}{x_t - x_{t-1}})$ is the direction of the arc $\overrightarrow{P_{t-1}P_t}$ in radian range of $[-\pi, \pi]$. Here, radian 0, $\frac{\pi}{2}$, π, and $\frac{3\pi}{2}$ represent upward, rightward, downward, and leftward directions, respectively.

2.2 Construction of Directional Histogram

Suppose we are given a codebook with K ($K = 72$) codewords, $\Theta = \{\theta_1, \theta_2, ..., \theta_k, ..., \theta_K\}$, where θ_k is set to cover the radian range $((k-1)\frac{2\pi}{K}, k\frac{2\pi}{K}]$. Let's quantize each directional feature O_t using Θ and represent the character sample as a sequence of discrete directional features. The intensity of feature θ_k is defined as

$$p(\theta_k) = \frac{1}{T}\sum_{t=1}^{T} I(O_t \in \theta_k),$$

where $I(\cdot)$ is an indicator function. It is then smoothed to deal with the sparse sample problem as follows:

$$\tilde{p}(\theta_k) = \sum_{j=-J}^{J} p(\theta_{k+j})G(j) \ ,$$

where $G(j) = \exp\left[-\frac{2(j^2)}{\lambda^2}\right]$ is a window function. Control parameters J and λ are set as $J = 4$, $\lambda = 2$ in our experiments.

2.3 Character-Structure-Guided Orientation Estimation

In this subsection, we present an orientation estimation approach guided by character structures. Firstly, a set of local modes, $\{\varphi_i\}_{i=1}^{M}$ are detected (see [3] for more details) from the directional histogram, where $\tilde{p}(\varphi_1) > \tilde{p}(\varphi_2) > \cdots > \tilde{p}(\varphi_M)$. They are rearranged as $\{\dot{\varphi}_i\}_{i=1}^{M}$ in descending order of mode indices to facilitate later discussions. The possible character orientations are then estimated with the help of the assumed character structures. In this study, we limit the allowed rotation degrees within $\pm\frac{\pi}{3}$. The decision rules for character orientation estimation are listed case by case in the following, where the necessary control parameters are tuned on development set for the best performance.

Table 1. Decision rules for character orientation estimation when only one distinguished mode is detected from the directional histogram.

Conditions	Decision Rules
$\dot{\varphi}_1 < \frac{\pi}{2}$	$\dot{\varphi}_1 - \frac{\pi}{2}$
$\lvert\dot{\varphi}_1 - \bar{\varphi}\rvert < \frac{\pi}{3}$	$\dot{\varphi}_1 - \bar{\varphi}$
$\dot{\varphi}_1 > \frac{4}{3}\pi$	$\dot{\varphi}_1 - \frac{5}{4}\pi$

2.3.1 Case 1: Single Mode Exists

When only one distinguished mode is detected, the handwritten character is expected to have a simple structure like "–", "|", "/" or "\". The decision rules for orientation estimation are summarized in Table 1. For example, when the detected mode lies in $(\frac{4}{3}\pi, 2\pi]$, the character may have a structure "/" and the character orientation may be decided as $\phi_1 = \dot{\varphi}_1 - \frac{5}{4}\pi$. The variable $\bar{\varphi}$ is introduced here to represent the direction of the principal axes of the normal-position characters, such as $\frac{\pi}{2}$, $\frac{3}{4}\pi$, π or $\frac{5}{4}\pi$, respectively.

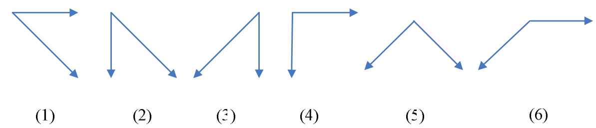

Figure 1. Possible character structures when 2 modes are detected from the directional histogram.

2.3.2 Case 2: Two Modes Exist

When two noticeable modes are detected, the possible character structures are illustrated in Fig. 1. Given the mode distribution, the possible character structures are assumed firstly. Then multiple character orientations are calculated by transforming the detected modes to the corresponding positions held by the principal axes of the normal-position characters. The detailed decision rules for orientation estimation are shown in Table 2. A new variable $\Delta\dot{\varphi}$, defined as $\dot{\varphi}_2 - \dot{\varphi}_1$, is introduced here to in-

Table 2. Decision rules for character orientation estimation when two noticeable modes are detected from the directional histogram.

Conditions				Decision Rules
$\Delta\dot{\varphi} < \frac{\pi}{3}$			$\frac{(\dot{\varphi}_1-\frac{\pi}{2})+(\dot{\varphi}_2-\frac{3}{4}\pi)}{2} < \frac{\pi}{3}$	$\frac{(\dot{\varphi}_1-\frac{\pi}{2})+(\dot{\varphi}_2-\frac{3}{4}\pi)}{2}$
			$\frac{(\dot{\varphi}_1-\frac{3}{4}\pi)+(\dot{\varphi}_2-\pi)}{2} < \frac{\pi}{3}$	$\frac{(\dot{\varphi}_1-\frac{3}{4}\pi)+(\dot{\varphi}_2-\pi)}{2}$
			$\frac{(\dot{\varphi}_1-\pi)+(\dot{\varphi}_2-\frac{5}{4}\pi)}{2} < \frac{\pi}{3}$	$\frac{(\dot{\varphi}_1-\pi)+(\dot{\varphi}_2-\frac{5}{4}\pi)}{2}$
$\frac{\pi}{3} < \Delta\dot{\varphi} < \frac{2}{3}\pi$	$\frac{\tilde{p}(\varphi_2)}{\tilde{p}(\varphi_1)} < 0.7$	$\tilde{p}(\dot{\varphi}_1) > \tilde{p}(\dot{\varphi}_2)$	$\dot{\varphi}_1 < \frac{\pi}{2}$	$\dot{\varphi}_1 - \frac{\pi}{2}$
			$\dot{\varphi}_1 > \frac{5}{6}\pi$	$\dot{\varphi}_1 - \frac{3}{4}\pi$
			$\frac{\pi}{2} \leq \dot{\varphi}_1 \leq \frac{5}{6}\pi$	$\{\dot{\varphi}_1 - \frac{\pi}{2}, \dot{\varphi}_1 - \frac{3}{4}\pi\}$
		$p(\dot{\varphi}_1) < \tilde{p}(\dot{\varphi}_2)$	$\dot{\varphi}_2 < \frac{5}{6}\pi$	$\dot{\varphi}_2 - \pi$
			$\dot{\varphi}_2 > \frac{4}{3}\pi$	$\dot{\varphi}_2 - \frac{5}{4}\pi$
			$\frac{5}{6}\pi \leq \dot{\varphi}_2 \leq \frac{5}{4}\pi$	$\{\dot{\varphi}_2 - \pi, \dot{\varphi}_2 - \frac{5}{4}\pi\}$
	$\frac{\tilde{p}(\varphi_2)}{\tilde{p}(\varphi_1)} \geq 0.7$		$\frac{(\dot{\varphi}_1-\frac{\pi}{2})+(\dot{\varphi}_2-\pi)}{2} < \frac{5}{18}\pi$	$\frac{(\dot{\varphi}_1-\frac{\pi}{2})+(\dot{\varphi}_2-\pi)}{2}$
			$\frac{(\dot{\varphi}_1-\frac{3}{4}\pi)+(\dot{\varphi}_2-\frac{5}{4}\pi)}{2} < \frac{5}{18}\pi$	$\frac{(\dot{\varphi}_1-\frac{3}{4}\pi)+(\dot{\varphi}_2-\frac{5}{4}\pi)}{2}$
$\Delta\dot{\varphi} > \frac{2}{3}\pi$	$\frac{\tilde{p}(\varphi_2)}{\tilde{p}(\varphi_1)} < 0.7$	$\tilde{p}(\dot{\varphi}_1) > \tilde{p}(\dot{\varphi}_2)$		$\dot{\varphi}_1 - \frac{\pi}{2}$
		$\tilde{p}(\dot{\varphi}_1) < \tilde{p}(\dot{\varphi}_2)$		$\dot{\varphi}_2 - \frac{5}{4}\pi$
	$\frac{\tilde{p}(\varphi_2)}{\tilde{p}(\varphi_1)} \geq 0.7$			$\frac{(\dot{\varphi}_1-\frac{\pi}{2})+(\dot{\varphi}_2-\frac{5}{4}\pi)}{2}$

dicate the possible character structures as explained in the following.

First, when $\Delta\dot{\varphi} < \frac{\pi}{3}$, the possible character structures may be the case (1), (2) or (3) shown in Fig. 1. Second, when $\frac{\pi}{3} \leq \Delta\dot{\varphi} < \frac{2\pi}{3}$, the possible character structures are the case (4) or (5) shown in Fig. 1. Two possibilities are considered in this case. If one mode dominates, satisfying $\frac{\tilde{p}(\varphi_2)}{\tilde{p}(\varphi_1)} < 0.7$, the character orientations are determined simply by the dominant mode. For example, if the first mode $\dot{\varphi}_1$ dominates, its corresponding normal position may be assumed as $\frac{\pi}{2}$ or $\frac{3\pi}{4}$. The orientation hypotheses could then be calculated accordingly. In another case when two modes are comparable, satisfying $\frac{\tilde{p}(\varphi_2)}{\tilde{p}(\varphi_1)} \geq 0.7$, an averaged orientation will be calculated instead. Lastly when $\Delta\dot{\varphi} > \frac{2}{3}\pi$, the character structure is possibly the case (6) in Fig. 1. Similarly, when $\frac{\tilde{p}(\varphi_2)}{\tilde{p}(\varphi_1)} < 0.7$, the character orientations are assumed by considering simply the dominant mode. Otherwise, an averaged distortion $\frac{(\dot{\varphi}_1-\frac{\pi}{2})+(\dot{\varphi}_2-\frac{5}{4}\pi)}{2}$ is used.

2.3.3 Case 3: Three Modes Exist

Fig. 2 illustrates all possible character structures when three modes are detected. Similarly, the possible character structures are firstly assumed according to the mode distribution. Then the character orientations are estimated by transforming the dominated mode to its corresponding normal position. For example when the first mode $\dot{\varphi}_1$ dominates, if $\dot{\varphi}_1 > \frac{5}{6}\pi$, the only possible character structure is the case (2) of Fig. 2. The character orientation is then calculated as $\phi_1 = \dot{\varphi}_1 - \frac{3}{4}\pi$ accordingly. In Table 3, we summarize the decision rules for character orientation

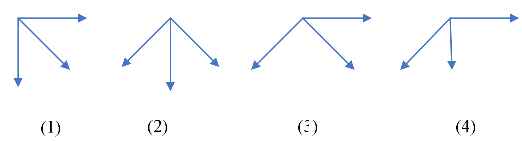

Figure 2. Possible character structures when 3 modes are detected from the directional histogram.

estimation when three noticeable modes are detected.

3 Experiments and Results

3.1 Experimental Setup

In order to demonstrate the effectiveness of the proposed character-structure-guided orientation estimation approach, a series of comparative experiments have been designed and conducted on the task of the recognition of isolated online handwritten characters with a vocabulary of 2965 level-1 Kanji characters in JIS standard. The popular Nakayosi and Kuchibue Japanese character databases [5] are used. The Nakayosi database consists of about 1.7 million character samples from 163 writers, and the Kuchibue database contains about 1.4 million character samples from 120 writers. We select randomly about 92% samples from the Nakayosi database to form the training data set, 75% samples from the Kuchibue database to form the testing data set T_0, while the remaining samples from both databases are used to form a development set for tuning control parameters. By this partition, there are

Table 3. Decision rules for character orientation estimation when three noticeable modes are detected from the directional histogram.

Conditions		Decision Rules
$\dot{\varphi}_1 = \varphi_1$	$\dot{\varphi}_1 < \frac{\pi}{2}$	$\dot{\varphi}_1 - \frac{\pi}{2}$
	$\dot{\varphi}_1 > \frac{5}{6}\pi$	$\dot{\varphi}_1 - \frac{3}{4}\pi$
	$\frac{\pi}{2} < \dot{\varphi}_1 < \frac{5}{6}\pi$	$\{\ \dot{\varphi}_1 - \frac{\pi}{2}\ ,\dot{\varphi}_1 - \frac{5}{6}\pi\ \}$
$\dot{\varphi}_2 = \varphi_1$	$(\dot{\varphi}_2 - \dot{\varphi}_1) < \frac{5}{12}\pi$	$\{\dot{\varphi}_2 - \frac{\pi}{2}, \dot{\varphi}_2 - \frac{3}{4}\pi, \dot{\varphi}_2 - \pi\}$
	$\frac{5}{12}\pi < (\dot{\varphi}_2 - \dot{\varphi}_1) < \frac{2}{3}\pi$	$\dot{\varphi}_2 - \pi$
	$\frac{2}{3}\pi < (\dot{\varphi}_2 - \dot{\varphi}_1) < \frac{3}{4}\pi$	$\{\dot{\varphi}_2 - \pi, \dot{\varphi}_2 - \frac{5}{4}\pi\}$
	$(\dot{\varphi}_2 - \dot{\varphi}_1) > \frac{3}{4}\pi$	$\dot{\varphi}_2 - \frac{5}{4}\pi$
$\dot{\varphi}_3 = \varphi_1$	$(\dot{\varphi}_3 - \dot{\varphi}_1) > \frac{5}{6}\pi$	$\dot{\varphi}_3 - \frac{5}{4}\pi$
	$(\dot{\varphi}_3 - \dot{\varphi}_1) < \frac{2}{3}\pi$	$\dot{\varphi}_3 - \pi$
	$\frac{2}{3}\pi < (\dot{\varphi}_3 - \dot{\varphi}_1) < \frac{5}{6}\pi$	$\{\dot{\varphi}_3 - \pi, \dot{\varphi}_3 - \frac{5}{4}\pi\}$

Table 4. Frequency distribution of estimation errors $\Delta\phi$ falling in each bin on 7 testing sets with various distortion degrees when using Nakagawa's approach for character orientation estimation.

	T_{-30}	T_{-20}	T_{-10}	T_0	T_{10}	T_{20}	T_{30}
Bin1	0.28	0.30	0.25	0.35	0.30	0.30	0.33
Bin2	0.37	0.35	0.40	0.26	0.33	0.34	0.30
Bin3	0.10	0.10	0.12	0.14	0.12	0.13	0.13
Bin4	0.06	0.06	0.06	0.06	0.06	0.05	0.06
Bin5	0.04	0.03	0.04	0.04	0.04	0.04	0.04
Bin6	0.04	0.04	0.03	0.03	0.03	0.03	0.04
Bin7	0.11	0.12	0.10	0.12	0.12	0.11	0.10

Table 5. Frequency distribution of estimation errors $\Delta\phi_{min}$ falling in each bin on 7 testing sets with various distortion degrees when using our proposed approach for character orientation estimation.

	T_{-30}	T_{-20}	T_{-10}	T_0	T_{10}	T_{20}	T_{30}
Bin1	0.31	0.31	0.31	0.31	0.32	0.32	0.33
Bin2	0.35	0.35	0.36	0.33	0.33	0.33	0.33
Bin3	0.17	0.17	0.16	0.22	0.19	0.19	0.19
Bin4	0.10	0.10	0.11	0.08	0.09	0.09	0.11
Bin5	0.05	0.05	0.05	0.05	0.06	0.05	0.03
Bin6	0.01	0.02	0.01	0.01	0.01	0.01	0.00
Bin7	0.01	0.00	0.00	0.00	0.00	0.01	0.01
Ave.#	2.00	2.01	1.98	1.92	1.83	1.74	1.73

704,650 samples in the training set, 229,398 in the development set, and 506,848 in the testing set, respectively. To simulate various rotations, additional 6 testing sets are generated artificially by rotating each testing sample in T_0 by $\pm 10^0$, $\pm 20^0$, $\pm 30^0$, respectively, which are denoted as $T_{10}, T_{-10}, T_{20}, T_{-20}, T_{30}, T_{-30}$, respectively.

Given a distorted sample $\mathbf{P}$, our proposed approach is used first to estimate $\hat{M}$ possible character orientations, denoted as $\{\hat{\phi}_i\}_{i=1}^{\hat{M}}$. For each hypothesis $\hat{\phi}_i$, the input sample $\mathbf{P}$ is then compensated as $\hat{\mathbf{P}}_i$ by transforming each sample point with the following transformation matrix:

$$W_{\hat{\phi}_i} = \begin{bmatrix} \cos(-\hat{\phi}_i) & -\sin(-\hat{\phi}_i) \\ \sin(-\hat{\phi}_i) & \cos(-\hat{\phi}_i) \end{bmatrix} .$$

Then, a 512-dimensional raw feature vector is extracted from each compensated sample $\hat{\mathbf{P}}_i$ using the approach in [2] which is an improved version of the approach proposed originally in [1]. A new 80-dimensional feature vector is then obtained via LDA (Linear Discriminant Analysis) transformation which is estimated by using training samples from 2965 Kanji characters. The same LDA transform is also used to construct a single-prototype (SP) based classifier, where the prototype for each character class is estimated as the sample mean of the corresponding training feature vectors. Such an SP-based classifier can be used to generate a short-list of top N candidates for each unknown and possibly distorted sample $\mathbf{P}$, where each compensated sample $\hat{\mathbf{P}}_i$ contributes $\frac{N}{\hat{M}}$ candidates different from the ones provided by other compensated samples.

3.2 Experimental Results

Let ϕ_{art} denote the artificial rotation degree, and ϕ_{est} the estimated one. Two frequency distributions of estimation errors, $\Delta\phi = |\phi_{art} - \phi_{est}|$ by using Nakagawa's approach [6, 7] and $\Delta\phi_{min} = \min|\phi_{art} - \phi_{est}|$ by using our proposed approach to estimate ϕ_{est}, are tabulated in Tables 4 and 5, respectively, where the bin starts from 0^0 with a bin size of 5^0. In the last row of Table 5, the average number of orientation hypotheses is also given for each testing set. Following observations can be made: 1) Compared with the single orientation estimated by Nakagawa's approach, our proposed approach gives a more accurate estimation due to the use of multiple hypotheses of the possible orientations; 2) The average number of the orientation hypotheses generated by our approach is about 1.89, which is small enough for practical applications.

After taking a close look, we noticed that our newly proposed character-structure-guided orientation estima-

Table 6. Comparison of "Top-N" character recognition accuracies (in %) on seven testing sets achieved by the conventional SP-based classifier without (Baseline) and with orientation compensation using Nakagawa's approach and our newly proposed approach respectively.

Different Approach	Size of Short-List	Testing Sets							
		T_{-30}	T_{-20}	T_{-10}	T_0	T_{10}	T_{20}	T_{30}	Ave.
Baseline	Top-6	17.42	67.27	97.54	99.35	98.14	74.67	23.73	68.30
	Top-12	24.23	75.27	98.57	99.60	98.94	81.42	31.62	72.81
	Top-100	53.63	91.99	99.77	99.93	99.84	94.35	65.32	86.40
Nakagawa Approach	Top-6	87.16	87.00	87.16	83.91	87.54	88.01	87.48	86.89
	Top-12	88.82	88.58	88.58	85.46	89.03	89.15	89.02	88.38
	Top-100	93.43	93.20	93.26	93.27	93.58	93.62	93.53	93.41
Our Approach	Top-6	95.49	95.54	96.04	96.20	95.99	96.17	96.92	96.05
	Top-12	96.91	96.97	97.35	97.44	97.29	97.45	98.01	97.35
	Top-100	98.93	98.97	99.12	99.13	99.08	99.20	99.44	99.13

tion approach exhibits different effect on various types of characters: 1). it works well on the characters with structures "$-$" and "$|$", such as "閑", "棡", "岨" and so on; 2). while for the characters with structure "/" or "\", e.g. "以", "及", "公", improvement may still be required.

Table 6 summarizes the "Top-N" character recognition accuracies (in %) of the conventional SP-based classifier constructed from the normal-position training samples. The baseline results are obtained without orientation compensation while other two sets of results are obtained with orientation compensation by using Nakagawa's method and our proposed approach respectively. The following observations can be made:

- Without orientation compensation, the performance of the conventional classifier degrades dramatically on distorted samples. The working range is about $[-10^0, 10^0]$;
- Compared with the baseline performance, using Nakagawa's approach for orientation compensation can improve greatly "Top-N" recognition accuracies on distorted samples. However, average accuracies of 86.89%, 88.38% and 93.41% for top-6, top-12 and top-100 candidates, respectively, are simply not good enough for many practical applications;
- Our approach achieves average recognition accuracies of 96.05%, 97.35% and 99.13% on top-6, top-12 and top-100 candidates, respectively, which are much better than that of Nakagawa's approach.

4 Summary

In this paper, we present a character-structure-guided approach to estimating the possible orientations of a rotated isolated online handwritten Chinese character. Different from the Nakagawa's approach which is effective only for a line of characters, our proposed approach is designed specially for dealing with the most challenging problem where only a single distorted Chinese character is available for orientation estimation. By using multiple hypotheses for orientation compensation, a very high "Top-N" recognition accuracy can be achieved for testing samples with various degrees of rotational distortions. Such "Top-N" lists generated for each testing sample can be used to facilitate other more advanced compensation approaches for robust handwriting recognition as described in [3].

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