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Improving Text-Independent Chinese Writer Identification with the Aid of Character Pairs

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Text-independent Chinese writer identification does not depend on the text content of the query and reference handwritings. In order to deal with the uncertainty of the text content, text-independent approaches usually give special attention to the global writing style of handwriting, rather than the properties of each individual character or word. Thanks to the existence of high-frequency characters, some characters probably appear in both the query and reference handwritings in most cases. If character images in the query handwriting are similar to those in the reference handwriting, this query handwriting and the corresponding reference handwriting are very likely to be written by the identical writer. In this paper, we exploit the above characteristic to improve the performance of Chinese writer identification. We first present an identification scheme using edge co-occurrence feature (ECF). Then, we detect the character pairs in the query and reference handwritings using a two-step framework and propose the displacement field-based similarity (DFS) to determine whether a character pair is written by the identical writer. The character pairs help to re-rank the candidate list obtained by text-independent ECF-based similarity and finally decide the writer of the query handwriting. The proposed method is evaluated on the HIT-MW and CASIA-2.1 datasets. Experimental results

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demonstrate that our proposed method outperforms the existing ones, and its Top-1 accuracy on the two datasets reaches 97.1% and 98.3%, respectively.

Keywords: Text-independent; Chinese writer identification; character pairs; edge co-occurrence feature; displacement field-based similarity.

1. Introduction

The requirements of personal authentication for information security have placed biometrics at the center of the academic and industrial research.[24] Biometrics refers to the automatic identification or verification of persons using their individual physical or behavioral characteristics. An ideal biometric should be universal, where each person possesses the characteristic; unique, where nobody should share the same characteristic; permanent, where the characteristics should not change over time; and collectable, where the characteristics should be quantifiable and easy to obtain.[23] It appears that handwriting cannot completely satisfy all the characteristics. However, handwriting is the most widespread carrier of personal behavioral information. People always have needs of daily writing, and the growing popularity of digital cameras and smartphones makes the collection of handwriting more and more convenient. For these reasons, handwriting is still an effective way to represent the uniqueness of individuals, and plays an essential role in biometric authentication.

Writer identification is a branch of behavioral biometrics using handwriting as the individual characteristic for authentication. It performs a one-to-many search in a dataset of reference handwritings of known authorships and returns a candidate list of the handwritings that is likely written by the identical writer of the query handwriting (see Fig. 1). The candidate list can be further inspected by the forensic expert who makes the final decision regarding the authorship of the query.[5]

In terms of data acquisition, writer identification can be classified into two categories: on-line and off-line. On-line data are collected at the same time when the

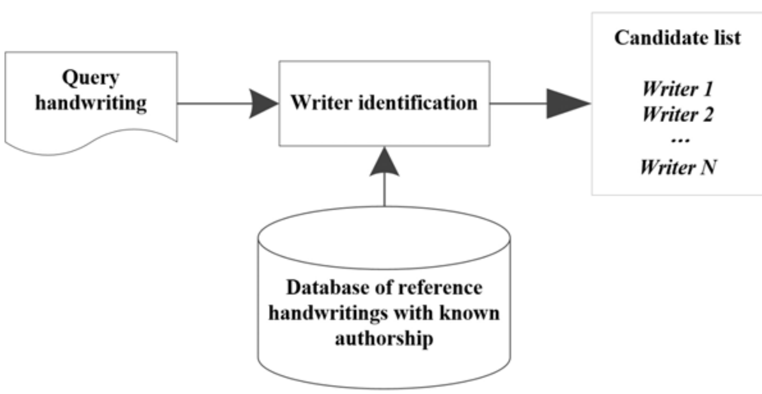


Fig. 1. Writer identification retrieves the handwritings of known authorships that are most similar to the query handwriting.

handwriting is produced. The writer creates handwriting via a mouse or an electronic pen, and the on-line data contains both sequential and spatial information. Off-line data refers to static image of handwritten document that is captured by a scanner or a camera. The limitation of on-line data acquisition makes on-line writer identification not suitable for the applications of forensic and historic document analysis, because it is unrealistic to collect the forensic and historic on-line data in most cases. Furthermore, writer identification can be divided into two categories: text-dependent and text-independent.[32] Text-dependent methods require that the text content of the query and reference handwritings he totally the same, and focus on the direct comparison of particular characters or words. On the other hand, text-independent methods are unconstrained with the text content, and employ features extracted from the whole image or regions of interest to describe the traits of the handwriting. However, they require a minimum amount of text to make a reliable decision.[2,13,14]

Chinese is one of the most widely used languages in the world. Chinese handwriting is a hieroglyphic writing. The stroke shapes and structures of Chinese characters are quite different from those of cursive writing. Due to the universality and complexity of Chinese handwriting, text-independent Chinese writer identification is still an attractive but also challenging task.

1.1. *Related work*

On the basis of the employed features, the existing approaches of text-independent writer identification can be roughly divided into two categories: texture-based approaches and shape-based approaches.[40]

When texture features are used, the handwriting is characterized by a series of texture properties. Bulacu and Schomaker[4] proposed the contour-hinge feature that consider both edges emerging from the central edge pixel. Fiel and Sablatnig[11,12] utilized the SIFT descriptors for both writer identification and writer retrieval. Djeddi *et al.*[9] extracted the run-length features from the gray-level run matrix to describe the characteristics of handwriting. Newell and Griffin[31] adopted oriented Basic Image Feature Columns for feature extraction, and enhanced the performance by encoding the writer's style as the deviation from the mean encoding for the population of writers. Christlein *et al.*[6,7] used the RootSIFT-based Gaussian Mixture Model (GMM) supervectors to encode the features to describe the characteristics of the handwriting, and trained the document-specific similarity measure by Exemplar-SVMs. He and Schomaker[16] proposed two curvature free features: run-lengths of Local Binary Pattern (LBP) and Cloud of Line Distribution (COLD) features for writer identification.

When shape features are used, the handwriting is characterized as a group of segmented shapes. Schomaker and Bulacu[33] proposed the connected-component contours to describe the shape of allographs. Abdi and Khemakhem[1] synthesized graphemes using beta-elliptic model rather than clustering original graphemes from the segmented handwriting. Instead of generating one single codebook, Khalifa *et al.*[25] utilized an ensemble of codebooks to describe the properties of handwriting. He *et al.*[19] proposed a method to detect the junctions in the stroke fragments, and used the probability distribution of junctions to distinguish different writers.

Meanwhile, with the emergence of deep learning, several approaches also attempted to realize writer identification using Deep Neural Networks (DNNs). Unlike traditional methods, DNNs learn feature mapping from training data directly. Compared with hand-designed feature descriptors, learning-based feature representation can exploit more data-adaptive information from training data. Christlein *et al.*[8] used Convolutional Neural Networks (CNNs) to learn the activations of the hidden layers and encoded them to feature vectors by GMM supervector encoding for classification. Fiel and Sablatnig[10] used the output of the second-to-last fully connected layer as the feature vector for writer identification.

For the issue of Chinese writer identification, researchers extensively investigated a series of frequency domain texture features in the early studies. Zhu *et al.*[44] used the two-dimensional Gabor filtering technique to extract texture features and a weighted Euclidean distance classifier to fulfill the identification task. Shen *et al.*[34] improved the Gabor filters with the wavelet technique to reduce the excessive calculational cost, and K Nearest Neighbor (KNN) classifier was utilized to identify the writer. He and Tang[18] used both autocorrelation function and Gabor filters to extract the features, and the weighted Euclidean distance classifier was used to match the extracted features. He *et al.*[20] presented Hidden Markov Tree Model in wavelet domain for Chinese writer identification. Compared with the two-dimensional Gabor model, the HMTM not only achieved better identification performance but also greatly reduced the elapsed time. After that, they also presented a wavelet-based method with generalized Gaussian density model.[21] Zhang *et al.*[43] proposed a hybrid method combining Gabor model with mesh fractal dimension.

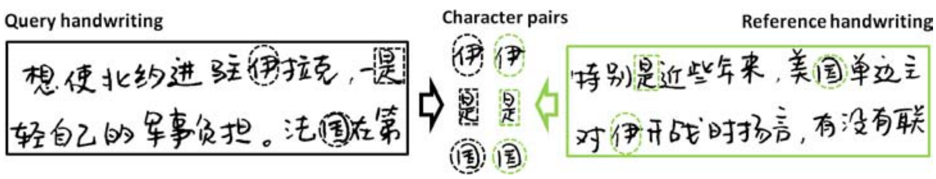
However, the performance of frequency domain texture features drops quickly when the number of writers becomes larger.[17] In order to solve this problem, Li and Ding[26] proposed a histogram-based feature called as Grid Microstructure Feature (GMF) extracted from the edge image, and the similarity of different handwritings was measured with the improved weighted Chi-squared distance. Xu *et al.*[41] proposed an inner and inter class variances weighted feature matching method to solve this problem. Wen *et al.*[38] characterized the frequent structure distribution of edge fragments on multiple scales to describe the writing style of Chinese handwriting, and applied Chi-squared distance as similarity measurement. Hu *et al.*[22] employed the SIFT descriptor to describe the local directional information of Chinese characters, and KNN classifier was used to identify the author of the handwriting. Instead of hard voting, they also presented two coding strategies for feature coding. Wu *et al.*[39] extracted the word-based SIFT from the handwriting and adopted the Manhattan and Chi-square distance to measure the similarity between the query and reference handwritings. Similarly, Tang *et al.*[36] used both

SIFT and triangular descriptors for feature extraction and Chi-square distance for similarity calculation.

1.2. *Our motivation*

By investigating the text contents of both the query and reference handwritings, we observe that some high-frequency Chinese characters probably appear in both the query and reference handwritings in most cases. We define the two characters appearing in the query and reference handwritings and being written by the identical writer, as a CP. Figure 2 presents two handwritings of writer A and two handwritings of writer B. There are three CPs ('伊', '是', '国') of writer A in Fig. 2(a) and two CPSs ('和', '在') of writer B in Fig. 2(b). Character pairs are usually ignored by the existing text-independent writer identification methods. In this paper, our motivation is to utilize CPs to improve the performance of text-independent identification. Although text-independent writer identification methods are independent of text content, the CPs surely benefit text-independent identification in the case that there exist such CPs. If no CP exists, the identification result is determined by the text-independent features only.

The outline of the proposed method is illustrated in Fig. 3. It contains two parts: ranking by Edge Co-occurrence Feature (ECF) and re-ranking with the aid of CPs. Firstly, ECFs of query and reference handwritings are extracted. Then, the weighted Chi-squared distance is employed to measure the similarities of these features. The ECF-based similarity of the query and reference handwritings are used to determine whether the reference handwriting matches with the query handwriting. For each query handwriting, we obtain a candidate list of the first N reference handwritings. Afterwards, we detect the CPs using a two-step scheme. Characters in the query handwriting are treated as examples, and are compared with all the characters in the reference handwriting to find its instances. All detected CPs contribute to the



(a) Character pairs (CPs) of writer A.

(b) CPs of writer B.

Fig. 2. Examples of CPs appearing in both the query and reference handwritings.

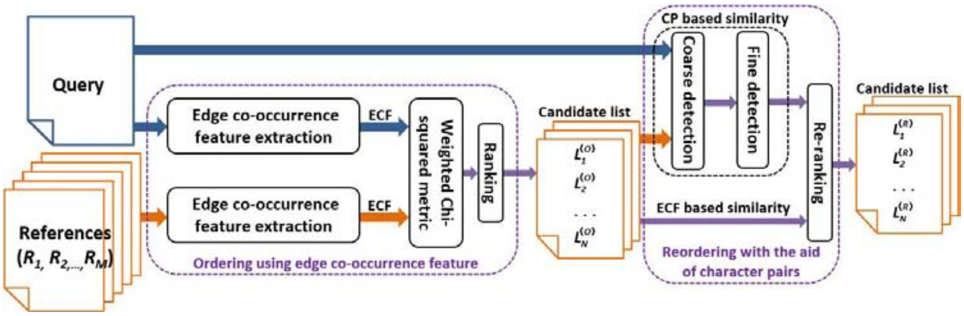


Fig. 3. The outline of the proposed method.

CP-based similarity between the query and reference handwritings. The CP-based similarity is fused with the ECF-based similarity to generate the final similarity between the query and reference handwritings. Finally, the candidate list of reference handwritings is re-ranked with the aid of CPs. The writer of the first reference handwriting in the new list is considered as the most possible writer of the query handwriting.

The remainder of this paper is organized as follows. Ranking by ECF is presented in Sec. 2. Re-ranking with the aid of CPs is described in Sec. 3. Experimental results are given in Sec. 4, and Conclusion is drawn in Sec. 5.

2. Ranking by ECF

We extract ECFs of the query and reference handwritings, and calculate the similarities of these features using the weighted Chi-squared distance. By ranking the ECF-based similarities between the query and reference handwritings in the descending order, we obtain a candidate list for each query handwriting.

2.1. *Edge co-occurrence feature extraction*

In this paper, we propose ECF, which is a histogram-based feature, for text-independent Chinese writer identification. The idea of ECF is derived from the contour-hinge feature[4] and the GMF.[26] The contour-hinge feature concerns the directions of two-linked edge fragments. The GMF focuses on the positions of edge pixel pairs. Differently, the proposed ECF characterizes the handwriting by the distribution of Co-occurrence Edge Pixel Pairs (CEPPs), which take into account not only the directions but also the positions of the edge pixels.

Figure 4 shows an example of extraction of the ECF. There is a window of 5×5, where its center pixel is an edge pixel (see Fig. 4(a)). The black block is the center pixel P, and the gray ones are other edge pixels. The pixel in the window is denoted as (w, θ), where w is the chessboard distance from P to the pixel and θ is the angle between the line from P to the pixel and the horizontal line. There are two edge pixels $\varepsilon = (w_\varepsilon, \theta_\varepsilon)$ and $\eta = (w_\eta, \theta_\eta)$. If ε and η are separated under the 4-direction connection and $w_\varepsilon = w_\eta$, (ε, η) is defined as a CEPP. As illustrated in Figs. 4(b) and 4(c),

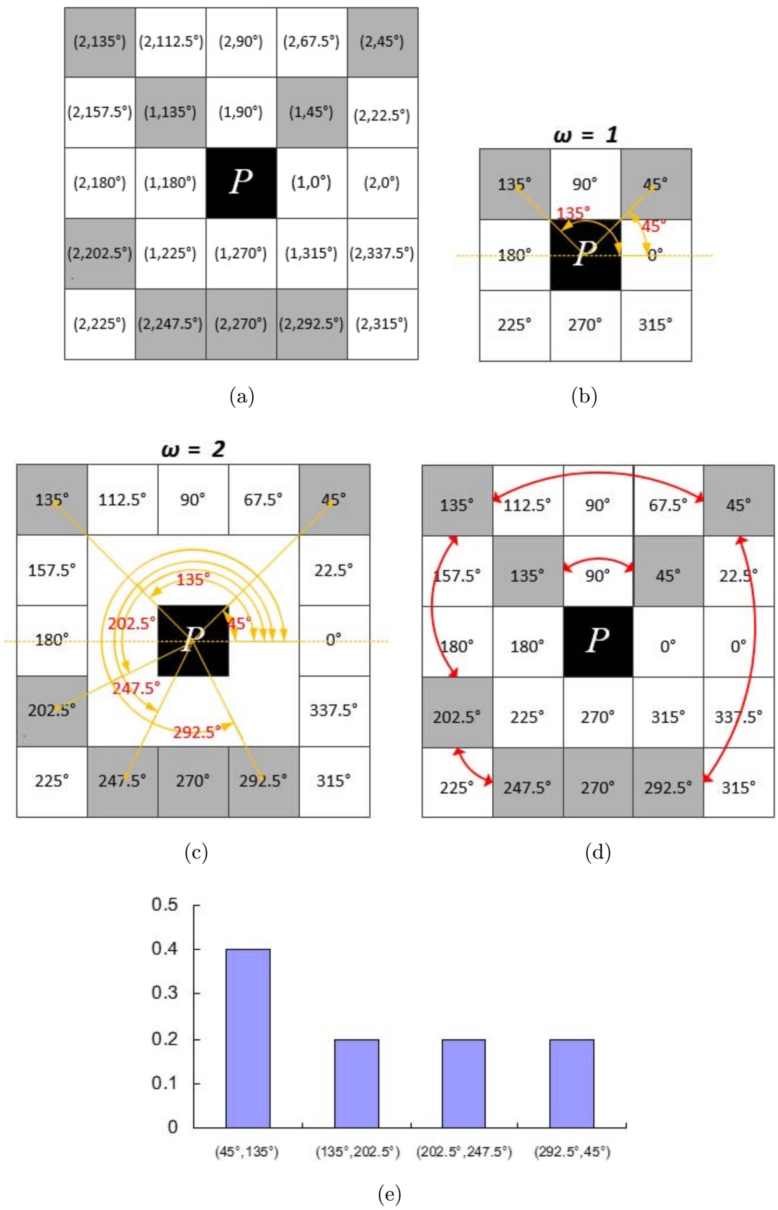


Fig. 4. An example of extracting ECF. (a) Edge pixels in 5×5, window, (b) CEPP: $(45°, 135°)$, (c) CEPPs: $(45°, 135°)$, $(135°, 202.5°)$, $(202.5°, 247.5°)$, $(292.5°, 45°)$, (d) CEPPs: $(45°, 135°)$, $(45°, 135°)$, $(135°, 202.5°)$, $(202.5°, 247.5°)$, $(292.5°, 45°)$ and (e) The distribution histogram of CEPPs.

when $w = 1$, there is one CEPP $(45°, 135°)$; when $w = 2$, there are four CEPPs, viz. $(45°, 135°), (135°, 202.5°), (202.5°, 247.5°)$ and $(292.5°, 45°)$.

In the procedure of feature extraction of the handwriting image, the angle of each pixel in the window is denoted as $\theta_1, \theta_2, \ldots, \theta_Y$, where Y is the number of different angles in the window. A series of bins are initialized and denoted as $\{\mathbb{B}_{j,k} = 0 \,|1 \leq j \leq k \leq Y\}$. The co-occurrence edge pixel pairs (ε, η) contained in the window are recorded in the corresponding $\mathbb{B}_{j,k}$. After the window has traversed all the edge pixels in the handwriting, the sum $\mathbb{S}$ of all $\mathbb{B}_{j,k}$ is calculated as

$$\mathbb{S} = \sum_{j,k}^{1\leq j\leq k\leq Y} \mathbb{B}_{j,k}. \tag{1}$$

The normalized bins $\{\frac{\mathbb{B}_{j,k}}{\mathbb{S}}|1 \leq j \leq k \leq Y\}$ are regarded as the ECF vector (see Fig. 4(d)). It can also be re-written as $(x_1, x_2, \ldots, x_Z)$, where Z is the dimension of the vector and $\sum_{z=1}^{Z} x_z = 1$. Each element x_z $(1 \leq z \leq Z)$ represents the occurrence probability of the corresponding CEPP.

2.2. *Ranking*

After ECFs of the query and reference handwritings are extracted, the weighted Chi-squared distance is applied to calculate their similarities. The query handwriting is denoted as Q, and the reference handwritings are denoted as $R_1, R_2, \ldots, R_M$, where M is the number of reference handwritings. ECFs of the query and reference handwritings are denoted as $\mathrm{ECF}_Q = (a_1, a_2, \ldots, a_Z)$ and $\mathrm{ECF}_{R_m} = (b_1^m, b_2^m, \ldots, b_Z^m)$, where $1 \leq m \leq M$. The weighted Chi-squared distance is used to calculate the similarity of ECFs between the query handwriting Q and the reference handwriting R_m

$$S_{\mathrm{ecf}}(Q, R_m) = \sum_{z=1}^{Z} \frac{(a_z - b_z^m)^2}{(a_z + b_z^m) * \sigma_z}, \tag{2}$$

where

$$\sigma_z = \sqrt{\frac{1}{M-1} \sum_{m=1}^{M} (b_z^m - \mu_z)^2}, \tag{3}$$

and

$$\mu_z = \frac{1}{M} \sum_{m=1}^{M} b_z^m. \tag{4}$$

The reference handwritings are ranked according to their similarities to Q in the descending order. The first N handwritings generate the handwritings in the candidate list, which is represented as $(L_1^{(O)}, L_2^{(O)}, \ldots, L_N^{(O)})$.

3. Re-Ranking with the Aid of CPs

We detect the CPs appearing in the query and reference handwritings. With the aid of CPs, we re-rank the candidate list $(L_1^{(O)}, L_2^{(O)}, \ldots, L_N^{(O)})$.

3.1. *Coarse detection of character pairs*

Character image in the query handwriting are treated as examples, and compared with all the character images in the reference handwriting. Geometric constraints including the aspect ratio and density of character images are applied to ensure that only the characters with similar aspect ratio and density can be considered, as in Eqs. (5) and (6). Assume that $\mathbb{Q}$ is a character image from the query handwriting and $\mathbb{R}$ is a character image from the reference handwriting. The heights, widths, and densities of $\mathbb{Q}$ and $\mathbb{R}$ are denoted as $H_{\mathbb{Q}}, W_{\mathbb{Q}}, D_{\mathbb{Q}}$ and $H_{\mathbb{R}}, W_{\mathbb{R}}, D_{\mathbb{R}}$, respectively.

$$\Delta_1 \leq D_{\mathbb{Q}}, \quad D_{\mathbb{R}} \leq 1 - \Delta_1, \tag{5}$$

$$\Delta_2 \leq \frac{H_{\mathbb{Q}}}{H_{\mathbb{R}}}, \quad \frac{W_{\mathbb{Q}}}{W_{\mathbb{R}}}, \quad \frac{D_{\mathbb{Q}}}{D_{\mathbb{R}}} \leq \frac{1}{\Delta_2}, \tag{6}$$

where Δ_1 and Δ_2 can be determined by the cross-validation.

Then, the binary normalized representation (BNR)[27] of character image is utilized for further comparison. The BNR of character image is implemented according to the following three steps. At first, the character image is normalized to the size of 8×8, and reshaped to a 1D vector of 64 elements. Then, the mean value of the obtained vector is calculated. At last, each element is compared with the mean value of the vector. If the value of the element is larger than the mean value, the element is binarized to 1. Otherwise, it is binarized to 0.

The BNRs of $\mathbb{Q}$ and $\mathbb{R}$ are denoted as $\mathrm{BNR}_{\mathbb{Q}}$ and $\mathrm{BNR}_{\mathbb{R}}$, and the Hamming distance $\mathbb{H}(\mathrm{BNR}_{\mathbb{Q}}, \mathrm{BNR}_{\mathbb{R}})$ between $\mathrm{BNR}_{\mathbb{Q}}$ and $\mathrm{BNR}_{\mathbb{R}}$ is used to determine whether $(\mathbb{Q}, \mathbb{R})$ is a potential CP. Only if $\mathbb{H}(\mathrm{BNR}_{\mathbb{Q}}, \mathrm{BNR}_{\mathbb{R}})/64 < \alpha$, $(\mathbb{Q}, \mathbb{R})$ is treated as a potential CP and will be taken into account for fine detection, where α is used to control the number of potential CPs.

3.2. *Fine detection of CPs*

With the potential CPs obtained by the coarse detection, we calculate the displacement field that aligns two characters of a potential CP using the Demons based algorithm.[37] Then, we propose the Displacement Field-based Similarity (DFS) of CP to determine whether a potential CP is written by the identical writer.

There are two character images $\mathbb{Q}$ and $\mathbb{R}$. Let us assume that there exists a displacement field s that provides a good alignment of $\mathbb{Q}$ and $\mathbb{R}$, if $\mathbb{Q}$ and $\mathbb{R}$ are the same characters written by the identical writer. The solution of s can be regarded as an optimization problem, and the energy function $E(c, s)$ is

$$E(c, s) = \frac{1}{\lambda_i^2} \|\mathbb{Q} - \mathbb{R} \circ c\|^2 + \frac{1}{\lambda_x^2} \|c - s\|^2 + \frac{1}{\lambda_T^2} \|\nabla s\|^2, \tag{7}$$

where λ_i stands for the noise on the image intensity, λ_x accounts for the spatial uncertainty, λ_T controls the amount of regularization, ∇s is the gradient of s, and $\circ$ is the compositive operation. The variable c is exact spatial transformation of s.

The minimization of $E(c, s)$ can be divided into two steps. The first step is to optimize $E_s^{\text{corr}}(c)$ with respect to c and fixed s, where

$$E_s^{\text{corr}}(c) = \frac{1}{\lambda_i^2} \|\mathbb{Q} - \mathbb{R} \circ c\|^2 + \frac{1}{\lambda_x^2} \|c - s\|^2. \tag{8}$$

Given the current transformation s, we need to compute c to minimize $E_s^{\text{corr}}(c)$. According to the theory of Ref. 37, $c = s \circ \exp(u)$ and $\|c - s\|^2 \approx \|u\|^2$ where u is the correspondence update field of s. Equation (8) can be rewritten as

$$E_s^{\text{corr}}(u) = \|\mathbb{Q} - \mathbb{R} \circ s \circ \exp(u)\|^2 + \frac{\lambda_i^2}{\lambda_x^2} \|u\|^2. \tag{9}$$

The intensity difference at each pixel p is defined as

$$\varphi_p(u) = \mathbb{Q}(p) - \mathbb{R} \circ s \circ \exp(u). \tag{10}$$

According to the first-order Taylor expansion,

$$\varphi_p(u) \approx \mathbb{Q}(p) - \mathbb{R} \circ s(p) + J^p u(p), \tag{11}$$

where $J^p = -\nabla_p^T(\mathbb{R} \circ s)$. With Eq. (11), $E_s^{\text{corr}}(u)$ can be reconstructed as

$$E_s^{\text{corr}}(u) \approx \frac{1}{|\Omega_p|} \sum_{p \in \Omega_p} \left\| \begin{bmatrix} \mathbb{Q}(p) - \mathbb{R} \circ s(p) \\ 0 \end{bmatrix} + \begin{bmatrix} J^p \\ \dfrac{\lambda_i(p)}{\lambda_x} \end{bmatrix} \cdot u(p) \right\|^2, \tag{12}$$

where Ω_p is set of the overlapped pixels between $\mathbb{Q}$ and $\mathbb{R} \circ s$. To obtain the minimum of $E_s^{\text{corr}}(u)$, the following equation should be satisfied

$$\begin{bmatrix} J^{p^T} & \dfrac{\lambda_i(p)}{\lambda_x} \end{bmatrix} \cdot \begin{bmatrix} J^p \\ \dfrac{\lambda_i(p)}{\lambda_x} \end{bmatrix} \cdot u(p) = \begin{bmatrix} J^{p^T} & \dfrac{\lambda_i(p)}{\lambda_x} \end{bmatrix} \cdot \begin{bmatrix} \mathbb{Q}(p) - \mathbb{R} \circ s(p) \\ 0 \end{bmatrix}, \tag{13}$$

which simplifies into

$$\left(J^{p^T} \cdot J^p + \frac{\lambda_i^2(p)}{\lambda_x^2} \right) \cdot u(p) = (\mathbb{R} \circ s(p) - \mathbb{Q}(p)) \cdot J^{p^T}. \tag{14}$$

Then, the update field u with the displacement field s is calculated as

$$u(p) = \frac{\mathbb{R} \circ s(p) - \mathbb{Q}(p)}{\|J^p\|^2 + \frac{\lambda_i^2(p)}{\lambda_x^2}} J^{p^T}, \tag{15}$$

where $\lambda_i(p)$ can be estimated as $|\mathbb{Q}(p) - \mathbb{R} \circ s(p)|$.

In order to smooth u, the fluid-like regularization is utilized, that is,

$$u = u * K_{\text{fluid}}, \tag{16}$$

where K_{fluid} is a Gaussian kernel and $*$ is the convolution.

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The second step is to optimize $E_c^{\text{corr}}(u)$ with respect to s and fixed c, where

$$E_c^{\text{corr}}(s) = \frac{1}{\lambda_x^2}\|c - s\|^2 + \frac{1}{\lambda_T^2}\|\nabla s\|^2. \tag{17}$$

This minimization of $E_c^{\text{corr}}(s)$ has a closed-form solution.[37] Given the harmonic regularization ∇s, the optimal deformation field s is the convolution of c by a Gaussian kernel K_{diff}, that is,

$$s = c * K_{\text{diff}}. \tag{18}$$

The displacement field s which aligns $\mathbb{Q}$ to $\mathbb{R}$ is calculated using the Demons-based iterations. Beginning with the initial state, the Demons-based iterations are performed until the iteration ℓ is equal to 0 (see Algorithm 1).

Then, we propose the DFS of CP to measure the similarity of CPs. The proposed $\text{DFS}_{(\mathbb{Q},\mathbb{R})}$ is defined:

$$\text{DFS}_{(\mathbb{Q},\mathbb{R})} = 1 - \frac{1}{\Psi}\|\mathbb{Q} - \mathbb{R} \circ s\|, \tag{19}$$

where Ψ is the normalization factor, and equals to the product of the size and gray scale of $\mathbb{Q}$. If $\text{DFS}_{(\mathbb{Q},\mathbb{R})} > \beta$, $(\mathbb{Q},\mathbb{R})$ is determined as a CP, β is the similarity threshold of the CPs.

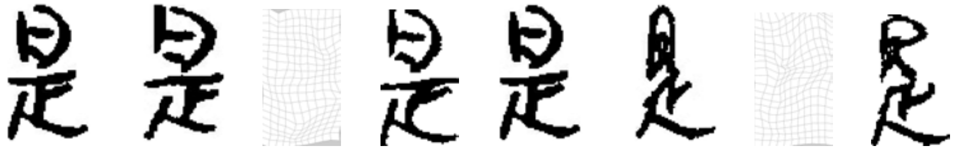
As shown in Fig. 5, there are two potential CPs $(\mathbb{Q},\mathbb{R}_1)$ and $(\mathbb{Q},\mathbb{R}_2)$. $\mathbb{Q}$ and $\mathbb{R}_1$ are written by the identical writer, but $\mathbb{Q}$ and $\mathbb{R}_2$ are not. The displacement field of $(\mathbb{Q},\mathbb{R}_1)$ is s_1 (see Fig. 5(b)), and that of $(\mathbb{Q},\mathbb{R}_2)$ is s_2 (see Fig. 5(e)). The aligned image $\mathbb{R}_1 \circ s_1$ of $\mathbb{R}_1$ is quite similar to $\mathbb{Q}$. Because the characters written by the identical writer are relatively consistent, and the deformation between $\mathbb{Q}$ and $\mathbb{R}_1$ can be recovered by compositing with s_1. However, the aligned image $\mathbb{R}_2 \circ s_2$ of $\mathbb{R}_2$ is still different from $\mathbb{Q}$. It is often the case that the DFS of characters of the identical writer

Algorithm 1. Demons-based iterations

Input: $\mathbb{Q}$, $\mathbb{R}$, s and ℓ.

Output: s

1: **repeat**
2: compute the update displacement field u by Eq. (15).
3: $u = u * K_{\text{fluid}}$ for fluid-like regularization, and the convolution kernel K_{fluid} is a standard Gaussian kernel.
4: $c = s \circ \exp(u)$.
5: $s = c * K_{\text{diff}}$ for diffusion-like regularization, and K_{diff} is a standard Gaussian kernel.
6: $\ell = \ell - 1$.
7: **until** ℓ is equal to 0.



(a) $(\mathbb{Q}, \mathbb{R}_1)$ (b) s_1 (c) $\mathbb{R}_1 \circ s_1$ (d) $(\mathbb{Q}, \mathbb{R}_2)$ (e) s_2 (f) $\mathbb{R}_2 \circ s_2$

Fig. 5. DFS of potential CPs $(\mathbb{Q}, \mathbb{R}_1)$ and $(\mathbb{Q}, \mathbb{R}_2)$.

is larger than that of the characters of different writers, which helps us to determine whether a potential CP is written by the identical writer.

3.3. *Re-ranking*

The query handwriting is denoted as Q, and reference handwritings in the candidate list are denoted as $(L_1^{(O)}, L_2^{(O)}, \ldots, L_N^{(O)})$, where N is the number of reference handwritings in the candidate list. Assume that the DFS of CPs appearing in Q and $L_n^{(O)}$ $(1 \le n \le N)$ are denoted as $\mathrm{DFS}_1, \mathrm{DFS}_2, \ldots, \mathrm{DFS}_{\mathrm{CP}(Q, L_n^{(O)})}$, where $\mathrm{CP}(Q, L_n^{(O)})$ is the number of CPs. The CP-based similarity $S_{\mathrm{cp}}(Q, L_n^{(O)})$ between Q and $L_n^{(O)}$ contributed by their CPs is expressed as

$$S_{\mathrm{cp}}(Q, L_n^{(O)}) = \frac{1}{\mathrm{CP}(Q, L_n^{(O)})} \sum_{c=1}^{\mathrm{CP}(Q, L_n^{(O)})} \mathrm{DFS}_c. \tag{20}$$

The ECF-based similarity $S_{\mathrm{ecf}}(Q, L_n^{(O)})$ between Q and $L_n^{(O)}$ is normalized as

$$S_{\mathrm{ecf}}(Q, L_n^{(O)}) = \frac{\min_{1 \le n \le N} S_{\mathrm{ecf}}(Q, L_n^{(O)})}{S_{\mathrm{ecf}}(Q, L_n^{(O)})}. \tag{21}$$

After that, the final similarity $S_f(Q, L_n^{(O)})$ between the query and reference handwritings is computed by

$$S_f(Q, L_n^{(O)}) = S_{\mathrm{ecf}}(Q, L_n^{(O)}) + \gamma * S_{\mathrm{cp}}(Q, L_n^{(O)}), \tag{22}$$

where $0 < \gamma < 1$ is the weight factor to adjust the contribution of CPs. According to the final similarity $S_f(Q, L_n^{(O)})$, the candidate list of the reference handwritings is re-ranked. The writer of the first reference in the re-ranked candidate list is considered as the most possible writer of the query handwriting.

4. Experimental Results

We employ the HIT-MW[35] and CASIA-2.1[28] to evaluate the proposed method. The HIT-MW dataset was first built for off-line Chinese handwritten text recognition, and is widely used for text-independent writer identification. In our experiment, the handwritings of 240 writers are employed for test. As done in Ref. 26, the first handwriting of each writer is segmented into two commensurate parts to create the query and reference samples. We also use CASIA-2.1 dataset to evaluate our method. The CASIA-2.1 dataset contains two sub-datasets, and the one created by 240 writers is used for the test. There are five handwritings for each writer. We only take the first two pages of each writer as the query and reference samples. Both datasets are divided into the query and reference sets, and every writer has only one image in each set. In order to investigate the influence of different settings on the identification performance and find the optimal parameters, all data within both datasets are used for the experiments.

Given a query handwriting Q, the system sorts all images in the reference set according to their similarities to Q. Ideally, the reference handwriting with the minimum distance should be written by the identical writer of Q. The ranking list (Top-n) is used to measure the performance of the proposed method. For the Top-n criterion, a correct hit is accumulated when at least one handwriting in the first n place of the ranking list is written by the correct writer. In our experiments, the Top-1, Top-5, and Top-10 are used to evaluate the performance of different methods.

The parameters Δ_1 and Δ_2 are determined by the cross-validation and set to 0.85 and 0.25, respectively. As for the parameter λ_x, the Demons-based algorithm works well in most cases when λ_x is in the range of $[0.25, 2]$. Thus, λ_x is set to 2. The size of the candidate list is set to 10.

4.1. *The influence of window size on ECF*

The size of window has an influence on the effectiveness of ECF. The local structure information is cracked when the size of window is too small, while the stroke information is rough when the window size is too large. A good choice of the window size is related to the character size of the handwriting. We use different sizes of windows to extract ECF from the handwritings and evaluate the performance of obtained features. Table 1 gives the Top-1 accuracy of ECF extracted from different window sizes on both datasets. When the size of window is 15×15, the identification accuracy is the highest. The reason for this phenomenon is that the height of the characters of the two datasets is in the range of $[40, 90]$ pixels. Thus, the size of 15×15 is capable to get both stroke and local structure information of characters.

Table 1. The accuracy of ECF extracted by different window sizes.

	Size				
Dataset	9×9	11×11	13×13	15×15	17×17
HIT-MW	93.8%	94.6%	95.0%	**95.8%**	95.4%
CASIA-2.1	94.2%	95.4%	95.8%	**97.1%**	96.3%

4.2. *The influence of different thresholds on character pair detection*

The threshold α as defined in Sec. 3.1 is used to control the number of potential CPs appearing in the query and reference handwritings. Coarse detection of CPs are designed for two purposes. The first is to detect as many real CPs as possible, while the second is to eliminate as many false CPs as possible. The former needs a relatively larger α, but the latter requires a smaller α. It implies that we have to make a trade-off between the efficiency and accuracy. In consideration that fine detection of CPs is utilized to eliminate false CPs, the first target is mainly considered in the selection of α. As shown in Fig. 6, the recall of CPs is used to evaluate the performance of the coarse detection with different values of α on two datasets. The higher the recall is, the more real CPs are included in the potential CPs. The values of α on two datasets is set to 0.36, empirically.

The threshold β as defined in Sec. 3.2 is utilized to determine whether a potential CP is written by the identical writer. The weight factor γ as defined in Sec. 3.3 is used to determine the contribution of CPs when computing the final similarity of the query and reference handwriting. Considering that both β and γ impact the identification performance of the system mutually, we carry out the following experiments to investigate the joint influence of β and γ. The Top-1 accuracy of the proposed method regarding different values of β and γ is given in Fig. 7. When β is smaller than 0.5, varying the value of γ has no influence on the performance. The reason for this phenomenon is that the coarse detection of CPs has already eliminated the false CPs with a low DFS before. As a consequence, the detected potential CPs that needs to be processed in the stage of the fine detection usually have a relatively high DFS (> 0.5). When β is between 0.5 and 0.7, some false CPs are incorrectly regarded as CPs that causes a great damage for the identification

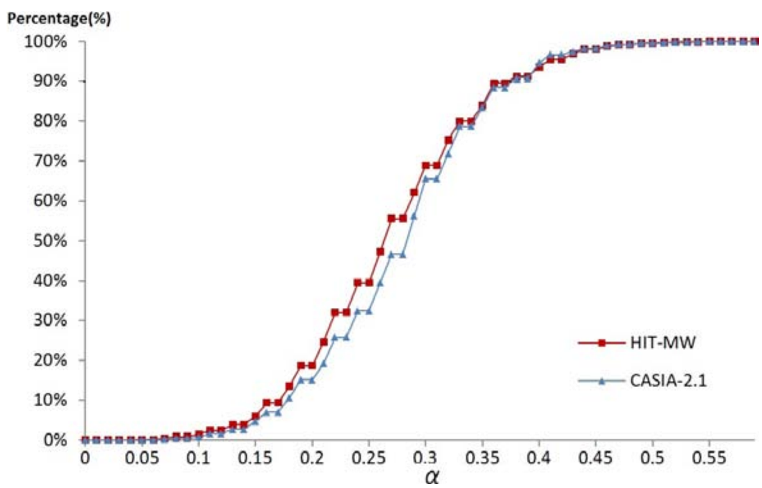
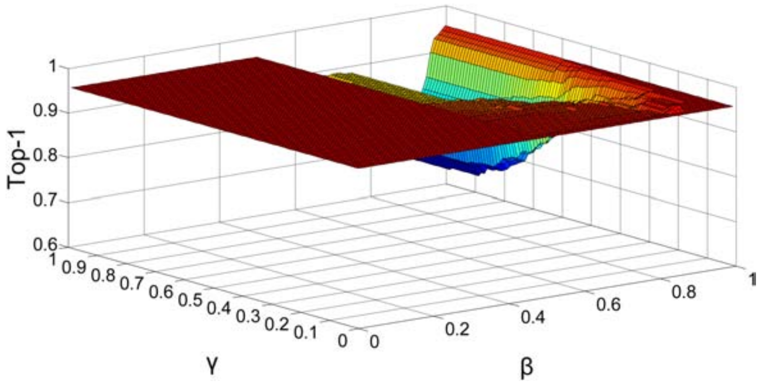
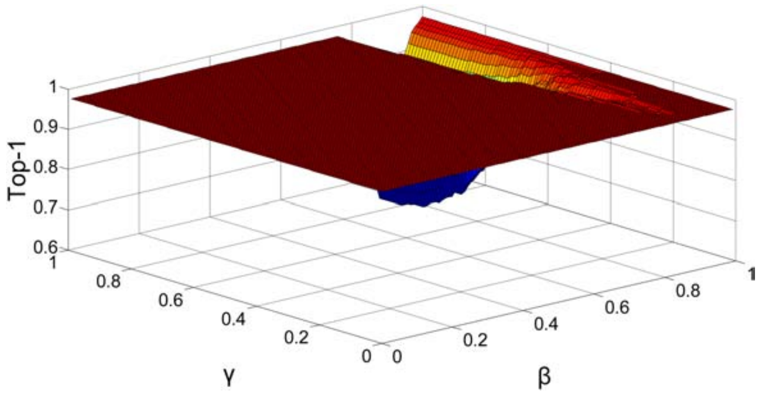


Fig. 6. The recall of CPs with different α on two datasets.



(a) On the HIT-MW dataset.



(b) On the CASIA-2.1 dataset.

Fig. 7. The Top-1 accuracy with respect to different values of β and γ on both datasets.

performance. When γ is larger than 0.2, it also leads to a drop of identification performance. Because the CP-based similarity is only a supplementary for writer identification, it should not cut down the effectiveness of ECF-based similarity. The best performance on the HIT-MW dataset is obtained when $\beta = 0.88$ and $\gamma = 0.05$. Correspondingly, the best performance on the CASIA-2.1 dataset is obtained when $\beta = 0.85$ and $\gamma = 0.15$.

4.3. *Performance of the proposed method on Chinese datasets*

We first compare the performance of our *pure* text-independent Chinese writer identification using ECF without the aid of CPs, with other existing approaches. Tables 2 and 3 show the Top-1, 5 and 10 accuracy of various methods on both datasets. Our best Top-1 accuracy on the HIT-MW and CASIA-2.1 datasets reaches 95.8% and 97.1%, respectively, which outperforms others. The results validate the discriminability of ECF.

Table 2. The performance of various methods without the aid of CPs on the HIT-MW dataset.

	Top-n		
Methods	Top-1 (%)	Top-5 (%)	Top-10 (%)
Contour-hinge[4]	84.6	95.4	96.7
GMF[26]	95.0	98.3	98.8
BOF[22]	95.4	**98.8**	**99.2**
ESC[38]	95.4	**98.8**	**99.2**
SOH+SDS[39]	95.4	**98.8**	**99.2**
The proposed ECF	**95.8**	98.3	**99.2**

Table 3. The performance of various methods without the aid of CPs on the CASIA-2.1 dataset.

	Top-n		
Methods	Top-1 (%)	Top-5 (%)	Top-10 (%)
GMF[26]	90.0	—	97.1
BOF[22]	96.3	—	**99.6**
The proposed ECF	**97.1**	**98.8**	**99.6**

To further investigate the effectiveness of CP detection method, we also compare the proposed method with other two related approaches that can also be applied to detect the CPs. The first approach utilizes the SIFT descriptors[29] of characters to determine whether potential CPs are written by the identical writer. The second approach extracts the HOG descriptors from characters and uses the two-directional dynamic time warping for character matching.[42] Tables 4 and 5 show the performance of the combinations of ECF with different CP detection methods on the HIT-MW and CASIA-2.1 datasets, respectively. The result shows that the performances are improved thanks to the combinations. It demonstrates that the CPs are beneficial to writer identification. Our best Top-1 accuracy on the HIT-MW and CASIA-2.1 datasets reaches 97.1% and 98.3%, respectively.

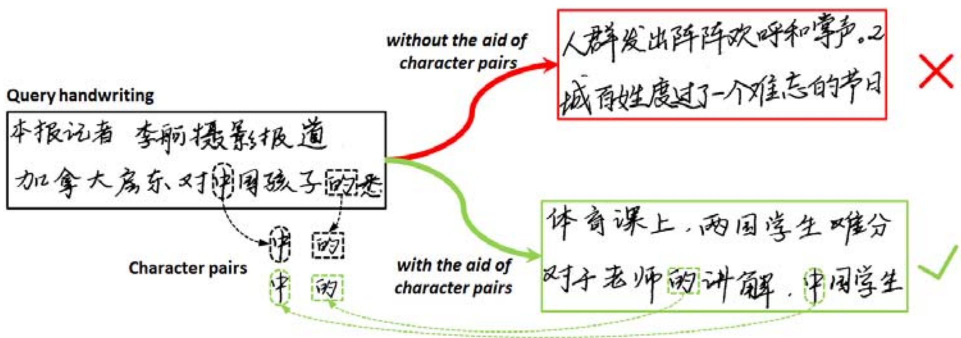
Table 4. The performance of the combinations of ECF with different CP detection methods on the HIT-MW dataset.

	Top-n		
Methods	Top-1 (%)	Top-5 (%)	Top-10 (%)
ECF + HOG	96.3	98.8	**99.2**
ECF + SIFT	96.7	99.2	**99.2**
ECF + DFS (proposed)	**97.1**	**99.2**	**99.2**

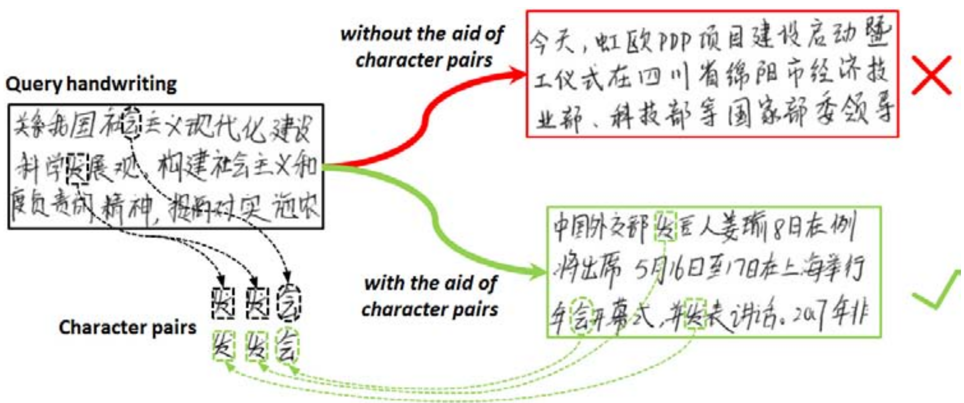
Table 5. The performance of the combinations of ECF with different CP detection methods on the CASIA-2.1 dataset.

	Top-n		
Methods	Top-1 (%)	Top-5 (%)	Top-10 (%)
ECF + HOG	97.5	99.2	**99.6**
ECF + SIFT	97.9	99.2	**99.6**
ECF + DFS (proposed)	**98.3**	**99.6**	**99.6**

Figure 8 shows two examples of handwritings that are correctly identified with the aid of CPs but incorrectly identified without the aid of CPs. When character images in the query handwriting are very similar to those in the reference handwriting, such two handwritings are likely to be written by the identical writer. It is obvious that the CPs are benefiting for improving the identification accuracy.



(a) An example from the HIT-MW dataset.



(b) An example from the CASIA-2.1 dataset.

Fig. 8. Examples from both datasets, which are incorrectly identified without the aid of CPs but correctly identified with the aid of CPs.

Table 6. The identification performance of various methods on the IAM dataset.

Methods	Top-1 (%)	Top-5 (%)	Top-10 (%)
Contour-hinge[4]	81.0	—	92.0
LPQ[15]	89.5	95.5	96.8
LBP + COLD[16]	89.9	—	96.9
Junclets[19]	91.1	—	97.2
GCF[25]	92.0	—	—
Fragment[14]	94.8	—	98.0
Quill–Hinge[3]	97.0	—	98.0
SOH + SDS[39]	98.5	99.1	99.5
ECF (proposed)	93.1	95.8	97.1
ECF + DFS (proposed)	95.2	96.8	97.1

4.4. *Application of the proposed method to English dataset*

In order to validate the reusability and robustness of the proposed method on other languages, we also test it on the IAM dataset.[30] A total of 1300 handwriting samples of 650 writers in the IAM dataset are used in our experiment. The detection of Chinese CPs is replaced by the detection of English word pairs. The corresponding β and γ are set to 0.77 and 0.04. We summarize the results of writer identification on the IAM dataset in the literature in Table 6. Comparison in Table 6 demonstrates that, though the proposed ECF is not outstanding for English writer identification, the performance is still improved with the aid of word pairs.

5. Conclusion

In this paper, we propose an effective method for Chinese writer identification. The proposed method realizes writer identification using ECF, and utilizes the CPs appearing in the query and reference handwriting to improve the identification performance. We put forward the concept of CP and propose a two-stage framework to detect the CPs. The coarse detection aims to detect potential CPs and the fine detection attempts to eliminate the false CPs. The proposed DFS is applied to determine whether the characters are written by the identical writer. CPs are surely beneficial to Chinese writer identification, but this characteristic is ignored by the traditional text-independent approaches on account of the uncertainty of the text content. We overcome the uncertainty problem skillfully by combining CPs with the proposed ECF, which is independent of the text content. With the aid of CPs, the identification performance of our method is satisfying. Our best Top-1 accuracy on the HIT-MW and CASIA-2.1 datasets reaches 97.1% and 98.3%, respectively, which outperforms other previous approaches. In addition, the proposed method also achieves promising results on the IAM English dataset, which implies that the proposed idea may be extended to other languages.

In this work, we assume that the locations of the characters in the handwriting is already provided. If they are not available, the process of character segmentation is indispensable prior to the detection of CPs. Furthermore, component/radical pairs may be considered instead of CPs for Chinese handwriting, to avoid the difficulty of character segmentation. In the future, we will further investigate this issue to make the proposed method more applicable.

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