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Beyond OCR: Multi-faceted understanding of handwritten document characteristics

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ABSTRACT

Handwritten document understanding is a fundamental research problem in pattern recognition and it relies on the effective features. In this paper, we propose a joint feature distribution (JFD) principle to design novel discriminative features which could be the joint distribution of features on adjacent positions or the joint distribution of different features on the same location. Following the proposed JFD principle, we introduce seventeen features, including twelve textural-based and five grapheme-based features. We evaluate these features for different applications from four different perspectives to understand handwritten documents beyond OCR (optical character recognition), by writer identification, script recognition, historical manuscript dating and localization. Extensive experimental results demonstrate that our novel QuadHinge and CoHinge features following the JFD principle provide promising results on these four applications.

1. Introduction

Nowadays, a large number of historical manuscripts have been digitized and technologies from pattern recognition have been applied to handwritten text search and retrieval. Automatic reading of the text context by OCR methods is not enough to completely understand handwritten manuscripts. In practice, current OCR systems are actually far from perfect anywhere, such that additional image information should be used in order to understand more of a given document. For example, writer, date and geographical provenance (location) are very important to correctly understand the valuable historical information contained in manuscripts by historians and paleographers [1].

Handwriting can be used as human behavioral biometrics measure [2] as the individual handwriting style is encoded into the handwritten patterns when they were written down. This allows for the analysis of the handwriting style of manuscripts based on handwritten texts to uncover the important context information, such as the writer, date and location. The main task of handwriting style analysis is to design handwriting style-specific features to extract visual attributes of writing. Feature representation maps raw pixels of characters into a discriminant high-dimensional space [3,4] which captures specific information of characters and can be processed by computers and it takes a very important role in pattern recognition and computer vision field. In fact, many efforts have been made to design discriminative and powerful features in computer vision [4]. Although it is shown that a (deep) learning-based feature representation may achieve significant results in various applications, the hand-crafted features are still very important in handwritten document analysis because the amount of data in historical manuscript collection is usually not big enough to train deep neural networks. For example, the ImageNet data set [5] contains several millions samples for training while most historical books contain only several thousands of pages. Particularly, historical manuscripts from ancient times are very rare and it is hard to use a complex data-intensive machine learning method to learn a shallow model which, with designed features, may be used on small collections. By harvesting classes using shallow methods, deep learning can be applied after a critical mass of data has been harvested.

In this paper, we propose a general joint feature distribution (JFD) principle, which allows researchers to design more powerful and discriminative features based on the existing feature extraction methods. Several novel features are proposed following the JFD principle, such as the CoLBP inspired by the co-occurrence pattern distributions [6], CoHinge and QuadHinge based on the original Hinge kernel [2], and the Ink Context inspired by the junction feature [7] and shape context [8]. We apply the existed and proposed features for multi-faceted understanding of handwritten manuscripts beyond OCR and evaluate these features from four perspectives: answering 4W questions in paleography and book history [1]: Who, Which, When and Where, corresponding to writer identification, script identification, dating and localization problems which can describe the historical context of manuscripts. Fig. 1 shows the four important questions without the OCR problem and their corresponding research problems.
2. Joint feature distribution principle

Previous studies [2,6,9–12] have shown that the use of spatial co-occurrence among features is more discriminative and powerful. In this paper, we extend this idea to the joint feature distribution principle (JFD principle), which can be divided into three different groups: the spatial joint feature distribution (JFD-S), the attribute joint feature distribution (JFD-A) and the joint kernel feature distribution (JFD-K).

We denote by \( f_i(x_j) \) the local feature on the position \( x_j \) in an image. Following the JFD-S principle, new features can be derived as:

\[
\begin{align*}
&f^{j_1,\ldots,j_n}(x_j) = [f_i(x_{j_1}), \ldots, f_i(x_{j_n})]_{\text{joint}}
\end{align*}
\]

where \( x_{j_1}, \ldots, x_{j_n} \) are \( n + 1 \) points on the image which have a certain spatial relationship and the new joint feature \( f^{j_1,\ldots,j_n}(x_j) \) captures more complex local structures with a larger supporting region.

Several feature methods followed the JFD-S principle have been proposed in the literature. For example, the Gray-Level Co-occurrence Matrices (GLCM) have been proposed for texture classification [9] and writer identification [13]. Pairwise local features have been studied for food recognition in [10] and co-occurrence of histogram of orientation gradient (HOG) has been studied in [11].

Following the JFD-A principle, new features can be derived as:

\[
\begin{align*}
&f^{j_1,\ldots,j_n}(x_j) = [f^{j_1}(x_{j_1}), \ldots, f^{j_n}(x_{j_n})]_{\text{joint}}
\end{align*}
\]

where \( f^{j_1}(x_{j_1}) \) and \( f^{j_n}(x_{j_n}) \) are different local features on the point \( x_j \) which may capture different attributes or properties. The attribute joint feature \( f^{j_1,\ldots,j_n}(x_j) \) usually has specific meanings. For example, the joint distribution of ink trace and ink width can capture the property of writing instruments [12]. In [14], the oriented Basic Image Feature Columns (oBIF Columns) which is the joint distribution of six Derivative-of-Gaussian filters at two scales has been applied for writer identification.

Following the JFD-K principle, new features can be derived as:

\[
\begin{align*}
&f^{j_1,\ldots,j_n}(x_j) = [K(f^{j_1}(x_{j_1}), f^{j_2}(x_{j_2})), \ldots, K(f^{j_1}(x_{j_n}), f^{j_2}(x_{j_n}+n))]_{\text{joint}}
\end{align*}
\]

where \( K(\cdot) \) is the kernel function which can describe the relationship between feature \( f \) on two different positions \( x_j \) and \( x_k \). Any kernel functions can be chosen and features with different kernel functions have different properties. For example, using the differential kernel operator based on the Hinge feature [2] derives the \( \Delta^H \) feature which is a rotation-invariant feature for writer identification.

The difference between the spatial joint feature \( f^{j_1,\ldots,j_n}(x_j) \) and the attribute joint feature \( f^{j_1,\ldots,j_n}(x_j) \) is that the spatial joint feature \( f^{j_1,\ldots,j_n}(x_j) \) is the joint distribution of the same type of feature \( f \) on different positions \( x_{j_1}, \ldots, x_{j_n} \) and the attribute joint feature \( f^{j_1,\ldots,j_n}(x_j) \) is the joint distribution of different types of features \( f^{j_1}, \ldots, f^{j_n} \) on the same position \( x_j \). The \( f^{j_1,\ldots,j_n}(x_j) \) inherits the properties of the \( f^{j_1}(x_j) \) feature. For example, if \( f^{j_1}(x_j) \) is sensitive to rotation changes, the \( f^{j_1,\ldots,j_n}(x_j) \) is also sensitive to rotations. However, using kernel functions, \( f^{j_1,\ldots,j_n}(x_j, \ldots, x_{j_n}, K) \) can introduce new properties or solve the transform invariant problems, depending on the definition of the kernel function \( K \).

One problem of the feature derived based on the JFD principle is that the feature dimension is very high. For example, if the dimension of \( f^{j_1}(x_j) \) is \( m \), the dimension of the joint feature \( f^{j_1,\ldots,j_n}(x_j) \) is \( m^{n+1} \). Therefore, \( n \) is usually set to 1, which results in the spatial co-occurrence features [6,9,10,12]. When \( n \) is large, the \( f^{j_1,\ldots,j_n}(x_j) \) describes large and complex structures in handwritten documents, which are called allographs or graphemes. The distribution of the allographs of documents is sparse in the feature space, which can be solved by the bag-of-word model [16] and the textual-based feature becomes the grapheme-based feature.

Following the proposed three principles, a feature network can be built, as shown in Fig. 2. Each node in the feature network represents the position on the image and can be described by the single feature \( f^{j_1}(x_j) \) or by the joint feature \( f^{j_1,\ldots,j_n}(x_j) \). Recursively using these three principles with proper local features and kernel functions, new and more abstract features can be derived directly from this feature network. For example, given the local feature \( f^{j_1}(x_j) \), a new feature \( f^{j_1,\ldots,j_n}(x_j) \) can be built using kernel function \( K \) by:

\[
\begin{align*}
&f^{j_1,\ldots,j_n}(x_j) = K(f^{j_1}(x_j), f^{j_2}(x_j)), \ldots, K(f^{j_1}(x_{j_n}), f^{j_2}(x_{j_n}+n))
\end{align*}
\]

where \( x_{j_1}, \ldots, x_{j_n} \) are spatially adjacent. The new feature \( f^{j_1,\ldots,j_n}(x_j) \) can also be considered as the local feature \( f^{j_1,\ldots,j_n}(x_j) \) to build more abstract features with the same or a different kernel function \( K' \). The \( \Delta^H \) feature network can be extended to a deeper network by recursively applying the JFD principle.
feature [15] is a typical example, where the $\Delta^\alpha$Hinge kernel can be computed directly from the $\Delta^\beta$Hinge kernel with the differential operator kernel function (see the $\Delta^\alpha$Hinge feature in Section 3).

3. Feature representation

In this section, we introduce several typical features developed in the literature for handwritten document analysis. In addition, we also propose several new features followed by the JFD principle. The features can be roughly categorized into two groups [2]: textural-based and grapheme-based methods and details of the computation are presented in following sections.

3.1. Textural-based features

Textural-based method considers the handwritten document as a textural image and extracts statistical information from text blocks on the entire image. Textural features extracted from handwritten images often capture the curvature and slant attributes of handwriting style and they usually do not need any segmentation method. Several typical textural-based features in the literature and their extensions are described in this section.

Local binary pattern (LBP) [17]: LBP is a gray-scale invariant textural feature and is widely used in texture recognition [18] and writer identification [19,20]. For a pixel $x_i$ in an image, the LBP code is defined as:

$$LBP_{p, r}(x_i) = \sum_{p=0}^{P-1} s(g_p - g_r) 2^p$$

where $g_p$ and $g_r$ are the pixel values of point $x_i$ and its neighbors, $P$ and $R$ are the number of neighbors and the radius of the neighbor pixels to the $x_i$, respectively. Following works [17,20], we set $P=8$ and $R=1$ and use LBP for short to represent LBP$_{8,1}$ thereafter. Finally, 255 patterns without the background one are considered to build the LBP histogram and the resulting descriptor is of dimension 255.

LBP follows the JFD-S principle, which joints the binary test $s(x)$ on eight neighbors of the certain pixel $x_p$:

$LBP(x_p) = \{s(x_1 - x_p), \ldots, s(x_8 - x_p)\}^{\text{joint}}$.

Co-occurrence local binary pattern (CoLBP): Following the JFD-S principle, we propose the co-occurrence LBP on handwritten documents, inspired by the work [6]. Given two pixels $x_i$ and $x_j$ with a Manhattan distance $l$ along the ink contour and their LBP uniform codes LBP($x_i$) and LBP($x_j$) (see Fig. 3), the CoLBP is defined as

$CoLBP(x_i, x_j) = [LBP(x_i), LBP(x_j)]^{\text{joint}}$.

The uniform LBP code is defined as the binary pattern where there is at most 2 bitwise transitions from 1 to 0 or vice versa [17]. The reason that we consider the uniform LBP code is that the most of LBP codes obtained along ink contours are uniform patterns. In order to make CoLBP rotation-invariant, we only consider the non-redundant patterns (LBP($x_i$) ≤ LBP($x_j$)). Finally, a 2D histogram is built to represent the probability of co-occurrence LBP patterns along ink contours and the dimension of the feature vector is $58^2(58+1)/2 = 1711$. The parameter $l$ is empirically set to 8 in our experiments.

Run-length histogram (RLH): Run-length features are widely used in handwritten document analysis [21–23]. The run-lengths of certain patterns along a given direction, such as ‘0’ and ‘1’ on binarized images, are quantized into a histogram as the feature representation. Usually, run-length histograms of ink and background pixels with the maximum length 100 are obtained on the horizontal and vertical directions and concatenated together as the final feature vector with the dimension of $2^2 \times 100 = 400$. The run-length feature follows the JFD-K principle, where the kernel function is defined to count the length of runs on the scanning direction.

Run-lengths of local binary pattern (LBPruns): The LBPruns feature has been proposed in our previous work [24], which computes the run-lengths of local binary patterns formed with $n$ parallel scanning lines along a given direction with inter-line distance $d$ on binarized images. Fig. 4 provides an example of LBPruns with three lines on the horizontal direction. The number of $n$ determines the number of possible local binary patterns and the inter-line distance $d$ determines the spatial resolution of local binary patterns. Finally, $2^n \times 2$ histograms on horizontal and vertical directions can be obtained and they are concatenated together to form the final feature vector. In this paper, we empirically set $n$ and $d$ to 5 and more detailed information of the selection of these parameters can be found in [24]. The maximum length $N_{\text{max}}$ is set to 100 (the discussion of the parameter is presented in Section 4.1.2) and the dimension of the final feature vector is $2^n \times 2 \times 100 = 6400$. The LBPruns feature follows the JFD-K principle, which builds the feature vector using the run-length method based on the LBP computations.

Hinge [2]: The hinge feature is the joint probability distribution of the orientations of legs of two contour fragments attached at a common end pixel on ink contours. Fig. 5 shows two examples of the Hinge kernel on contour fragments with leg length $l$ and the joint probability of the two orientations, $\alpha$ and $\beta$ ($\alpha < \beta$), are quantized into a 2D histogram. In this paper, we set $l=7$ and the number of bins of $\alpha$ and $\beta$ is set to 23. Finally, the dimension of the feature vector is 253. The Hinge feature follows the JFD-A principle, which considers two different directions (can be considered as two attributes) on each contour pixel.

Co-occurrence hinge (CoHinge) [25]: We provide a feature followed the JFD-S principle: the CoHinge, which is defined as the joint distribution of the Hinge kernel on two different points $x_i$ and $x_j$ with a Manhattan distance $l$ on contours, similar as the CoLBP feature:

$CoHinge(x_i, x_j) = [\text{Hinge}(x_i), \text{Hinge}(x_j)]$.

Each Hinge kernel has two values $\alpha$ and $\beta$, and therefore, the CoHinge kernel has four values $\{\alpha(x_i), \beta(x_i), \alpha(x_j), \beta(x_j)\}$, which can be quantized into a 4D histogram. The Manhattan distance $l$ is set to 7 (more information of this parameter is shown in Section 4.1.2). We set the

![Fig. 3. Co-occurrence patterns on ink contours.](image1)

![Fig. 4. Illustration of run-lengths of local binary pattern P1, P2 and P3 on the sequence S formed by three parallel scanning lines l_{p1}, l_{p2} and l_{p3} with d=6.](image2)
number of bins of the angle to 10, and finally the dimension of the CoHinge feature is $10^4 \times 10^4 = 10,000$.

$\Delta^3$Hinge: The $\Delta^3$Hinge is a rotation-invariant texture feature, which has been proposed in [15]. The $\Delta^3$Hinge feature can be computed from the feature network (see Fig. 2), with the differential operator between Hinge kernels as the kernel function $K$:

$$f^\alpha(\mathbf{s}) = K(f^{\alpha-1}(\mathbf{s}), f^{\alpha-1}(\mathbf{s} + \delta\mathbf{l})) = K(f^{\alpha-1}, \cdot)$$

(8)

where $f^\alpha(\mathbf{s}) = (\Delta^\alpha a, \Delta^\beta b)$ is the Hinge kernel and $n$ is the order of the differential operator. We use $K(f^{\alpha-1}, \cdot)$ for short representation and the $\Delta^3$Hinge can be recursively computed by:

$$f^\alpha(\mathbf{s}) = K(f^{\alpha-1}, \cdot) = K(K(f^{\alpha-2}, \cdot), \cdot) = K(K(K(f^{\alpha-3}, \cdot), \cdot), \cdot) = \cdots$$

(9)

where $f^0 = (a, b)$ is the original Hinge kernel [2]. More precisely, the $\Delta^3$Hinge kernel is defined as:

$$\Delta^3a(\mathbf{s}) = \frac{\Delta^{-1}a(\mathbf{s}) - \Delta^{-1}a(\mathbf{s} + \delta\mathbf{l})}{\delta\mathbf{l}}$$

$$\Delta^3b(\mathbf{s}) = \frac{\Delta^{-1}b(\mathbf{s}) - \Delta^{-1}b(\mathbf{s} + \delta\mathbf{l})}{\delta\mathbf{l}}$$

(10)

Although many different features can be generated based on the feature network with different $n$, in this paper, we only report the performance of the $\Delta^3$Hinge feature and the feature dimension is 780.

**Triple chain code (TCC)** [26]: The chain code on a pixel of writing contours is the one of eight directions where the next pixel on, denoted as $f^{\alpha}(\mathbf{s})$.

$$TCC(\mathbf{x}_i, \mathbf{x}_{i+1}, \mathbf{x}_{i+2}) = [\alpha(x_i), \alpha(x_{i+1}), \alpha(x_{i+2})]$$

(11)

where $\alpha(x_i) \in \{1, 2, \ldots, 8\}$ is the chain code value on position $x_i$ and $l$ is the Manhattan distance along writing contours. In this paper, we set $l$ to 7, the same as the value of the CoHinge feature. Finally, the feature dimension is $8 \times 8 \times 8 = 512$.

**Quill and QuillHinge** [12]: The Quill feature is the joint probability distribution $p(\mathbf{s}, \mathbf{w})$ of the relation between ink direction $\mathbf{w}$ and the ink width $w$, which captures the writing instrument property. It follows the JFD-S principle, because the feature types, the ink direction and ink width, are different. The QuillHinge is an extension of the Quill and Hinge, and it is the probability of $p(\mathbf{s}, \mathbf{w})$, resulting in a 3D histogram. We use the same parameters of the Quill and QuillHinge as the original paper [12], and the dimensions of Quill and QuillHinge are 1600 and 31,200, respectively.

**QuadHinge (QuadHinge)** [25]: We also provide the QuadHinge feature to demonstrate the power of the feature following the JFD-A principle. In order to incorporate the curvature information of two contour fragments in the Hinge kernel, we define a fragment curvature measurement (FCM) $C(\mathcal{F}_i)$ for contour fragments, inspired by [27]:

$$D(\mathcal{F}_i) = \frac{d(s)}{d(\mathcal{F}_i)}$$

where $d(\mathcal{F}_i)$ is the length of the Hinge kernel and $d(s)$ is the length of the contour fragments $s$.

$$\mathcal{F}_i = \frac{d(s)}{d(\mathcal{F}_i)}$$

(12)

as the proportion of the Euclidean distance $d(s)$ between two end points to the length of the contour fragments $s$. $C(\mathcal{F}_i)$ is defined for contour fragments, inspired by the Chebyshev distance between two neighbor pixels is equal to 1.

A novel QuadHinge kernel, which integrates the $C(\mathcal{F}_i)$ into the original Hinge kernel, defined as: $H(\mathcal{s}, \mathbf{w}) = (\alpha, \beta, C(\mathcal{F}_i), C(\mathcal{F}_j))$, where $p$ is the center point, $s$ is the fragment length, $C(\mathcal{F}_i)$ and $C(\mathcal{F}_j)$ are the fragment curvature measurements of the two contour fragments, respectively (see examples in Fig. 5). Adding the curvature information of the two contour fragments can improve the discriminative of the Hinge kernel. For example, the Hinge kernels $\{\alpha, \beta\}$ of the left and right fragments in Fig. 5 are the same. However, the curvatures of the fragments are different, yielding different QuadHinge Hinge kernels. Finally, the QuadHinge Hinge kernels on all contour pixels are collected and quantized into a 4-D histogram. In order to capture the scale information, we agglomerate the QuadHinge Hinge kernels with multiple scales, where the scale factor $s$ is set as: $s = s_{h}(t + 1)$. The $s_{h}$ is the basic fragment length and $t = 0, 1, \ldots, T$ and $T$ is the index of maximal scales. In this paper, we set the number of angle bins $N_\alpha$ to 12, the number of $C(\mathcal{F})$ bins $N_\mathcal{F}$ to 6, $s_{h} = 5$ and $T=10$, and the final feature dimension is $6 \times 6 \times 12 \times 12 = 5184$. More information of the selection of these parameters can be found in Section 4.1.2.

**Cloud of Line Distribution (COLD)** [56]: Inspired by the fact that writing contours can be approximated by a set of line segments obtained by the sequential polygonization algorithm [26] and the length and orientation of these straight lines can capture the handwriting styles, we introduce a new curvature-free feature called Cloud of Line Distribution (COLD). The COLD feature is the joint probability distribution of the length and orientation of these lines followed by the JFD-A principle and the computational procedure is described as follows (see Fig. 6): First, the ordered high-curvature points on the writing contours are obtained using the method [28], denoted by $\mathcal{P} = \{\mathcal{p}(i, j), i = 0, 1, 2, \ldots, n\}$, where $(i, j)$ is the coordinate of the
point \( p_k \). The line segments can be obtained between any pair of the dominating points \( (q_i, p_m) \), where \( k \) is the parameter which denotes the distance on the dominant sequence \( \mathcal{P} \). Each line can be measured by a pair \((\theta, \rho)\) in the polar coordinate space, where \( \theta \) is the line orientation and \( \rho \) is the line length. All lines in a given handwritten document can form a distribution in the polar coordinate space and can be quantized into a log-polar histogram inspired by the Shape Context [8]. The features obtained with \( k = 1, 2, 3 \) in the log-polar space with the radius 7 and the angular intervals 12 are concatenated into one feature vector with the dimension: \( 7 \times 12 \times 3 = 252 \).

### 3.2. Grapheme-based features

Grapheme-based features capture the statistical distribution of the allograph segmented from handwritten texts and it is assumed that individuals have their own prototypes in their brain to draw characters. Although any spatial co-occurrence feature can be generalized to the grapheme-based feature, in this section, we introduce several typical grapheme-based features for handwritten manuscript understanding. In fact, all the grapheme-based features follow the JFD-S principle, which concatenate the spatial information together to obtain a large structure of the ink trace.

**Connected-component contours (CO3)** [29]: The CO3 is the contour obtained from each connected component of the binarized handwritten image. In order to measure the similarity between CO3s, each CO3 is resampled to contain a fixed number of coordinate pairs \((x_i, y_i)\) and the normalized coordinate pairs can be considered as the feature vector:

\[
\tau = (x_i - \mu_x) / \sigma_x \\
\pi = (y_i - \mu_y) / \sigma_y
\]

where \( \mu_x \) and \( \mu_y \) are averages of the \( x_i \) and \( y_i \) coordinates and the \( \sigma_x \) and \( \sigma_y \) are the corresponding standard deviations. In this paper, we sample 100 points on each contour and the size of the contour descriptor is \( 2 \times 100 = 200 \).

**k contour fragments (kCF)** [30]: One limitation of the CO3 is that it is sensitive to the cursive handwriting where characters are always touched with each other and the resulting CO3’s are very large and less repeatable. In order to solve such a problem, we extract contour fragments from the handwritten text contours, inspired by [31]. The dominant points \( \mathcal{P} = \{p(x_i, y_i), i = 0, 1, 2, \ldots, n\} \) are obtained first, using the same method as in the GOLD feature. We compute break points \( \Theta = \{\theta_i(x_i, y_i), i = 0, 1, 2, \ldots, n\} \) as the midpoints of each pair of dominant point \((p_i, p_{i+1})\), and the contour fragments can be obtained between any pair of the break points \((b_i, b_{i+k})\), denoted as kCF. Similar as the CO3 method, 100 points are sampled from each contour fragment and normalized using the method described in Eq. (13) to describe each kCF.

**Junction features (Junclets)** [7]: Junction feature is the stroke-length distribution in every directions from 0 to \( 2\pi \) around a reference point (see Fig. 7) inside the ink trace. When the center point lies on the junction point, such as the fork point or high curvature point on the skeleton line of ink strokes, the corresponding feature is the junction feature, which contains the junction information around the joint point. In this paper, we compute the stroke length distribution in 120 directions equidistantly sampled from 0 to \( 2\pi \) and the feature dimension of each junction is 120.

**k stroke fragments (kSF)** [30]: The connected component of handwritten texts can be decomposed into fragments based on fork points. Fig. 8 shows an example of a connected component and seven primary stroke fragments are obtained by segmenting at the fork points, which are denoted by numbers 1–7. In order to extract longer and more complex stroke fragments, a stroke fragment graph (SFG) is built where the nodes correspond to the primary strokes and two nodes are linked if their corresponding stroke fragments connect to each other (an example is shown in Fig. 8(b)). From the SFG, we can obtain the more complex stroke fragments (kSF) from any connected subgraph in the SFG with the path length \( k \) without any loops. Then \( N_s \) reference points are sampled equidistantly on the skeleton line of the stroke fragment and each point is described by the junction feature. Finally, all the \( N_s \) junction features are concatenated together to form the final feature vector. In this paper, we set \( N_s \) to 10 and the size of the kSF descriptor is \( 120 \times 10 = 1200 \).

**Ink context (IC):** Given a reference point inside the ink, a scale-invariant log-polar space is built with the scale factor \( \omega \), which is the half stroke width on the reference point (see Fig. 9). The scale factor \( \omega \) can be computed by \( \omega = \min\{\text{len}(\theta_m)\} \), where \( \text{len}(\theta_m) \) is the stroke length in the direction \( \theta_m \). Inspired by the Shape Context [8], a coarse histogram is computed by counting the number of ink pixels in each bin of the log-polar space. In this paper, we set the parameters of the log-polar space as: the radius is set to 4 and the angular interval is set to 120. Finally, the size of the IC histogram is \( 4^1 \times 120 = 480 \).

For all the five grapheme-based features, we randomly select...
handwritten documents to train the codebook using the 2D Kohonen Self-Organizing Map (SOM) \([2,32]\) with the cell size \(30 \times 30 = 900\).

4. Applications

In this section, we evaluate the twelve textural-based features and five grapheme-based features to answer the 4W questions to understand the handwritten manuscript, corresponding to the writer identification, script identification, manuscript dating and localization problems.

4.1. Writer identification

Writer identification is to answer the question: “who wrote the given document?” according to the characteristic handwriting style encoded in the handwritten text and it has been widely studied in the literature \([21,29,22,26,12,7]\). Given the query handwritten document \(q_1\), where \(s_i\) is the script of the handwritten text and \(u_w\) is the writer which needs to be identified, all documents in the database \(p \in D^w\) with labels of writer \(u_w\) and script \(s_i\) are sorted according to the feature distance between \(q_1\) and \(p^w\) to output a hit list where the writer of the top document is assigned to \(u_w\). In this paper, three different experimental settings are considered as follows:

- Writer identification based on single-script. Both the query document \(q_1\) and documents on the database \(p^w \in D^w\) are written with the same script \(s_i\).
- Writer identification based on mixed-scripts. Both the query document \(q_1\) and documents on the database \(p^w \in D^w\) are written with two different scripts \((s_i, s_j)\).
- Writer retrieval. For the query handwritten document \(q_1\), there are more than one document from the same hand on the database \(D^w\). For the task of writer retrieval, our aim is to retrieve the list of handwritten documents which are from the same hand with the query document \(q_1\).

Writer identification is performed in a “leave-one-out” manner \([2,7,12,26]\): taking the query document out and sorting the rest documents according to the distance function to output a hit list. The query document is recognized as the writer of the document on the top \(x\) of the hit list, corresponding to the Top-\(x\) performance. In this paper, Top-1 and Top-10 are adopted in all experiments. \(\chi^2\) distance is used because it is the best distance function for the probability feature vector \([2]\).

4.1.1. Data sets

Several public databases are available for writer identification, such as the Firemaker \([33]\), IAM \([34]\), CERUG \([7]\), ICFHR2012 Arabic data set \([35]\) and ICDAR2013 \([36]\). The Firemaker set contains four pages of handwriting written by 250 Dutch subjects: page 1 and page 4 contain lower-case letters, page 2 was written by only uppercase letters, and page 3 contains the “forged” text. We use the page 1 vs 4 in our experiments, similar as works in \([2,7,12]\). The IAM set contains 650 writers written in English, modified following the work \([2]\) from the original IAM database \([34]\). The CERUG set is a cross-script data set, written by 105 Chinese subjects on four pages: page 1 and page 2 were written in Chinese, page 3 contains the English text and page 4 contains both Chinese and English characters. The data set used for the ICFHR2012 competition on writer identification with Arabic scripts \([35]\) contains 204 writers and we only use the first two paragraphs to perform writer identification. The data set used for the ICDAR2013 competition on writer identification \([36]\) contains 250 writers with four pages (2 English and 2 Greek).

4.1.2. Parameter evaluation

In this section, we present the evaluation of the parameter selection for different features.

Fig. 10 shows the Top-1 performance of writer identification on the Firemaker data set with different maximum run-length \(N_{max}\). From the figure we can find that the performance is quite stable when \(N_{max}\) is \([40, 120]\). As mentioned above, we set it to 100, following the work \([22]\).

Fig. 11 shows the Top-1 performance of writer identification on the Firemaker data set with different Manhattan distances \(l\) between two different points \(x_i\) and \(x_j\) of the CoHinge feature. From the figure we can find that \(l=7\) provides the optimal result.

There are four parameters of the QuadHinge feature: the number of angle bins \(N_{\alpha}\), the number of curvature \(c(T)\) bins \(N_t\), the maximal scale \(T\) and the basic fragment length \(s_b\). Fig. 12 shows the performance of writer identification on the Firemaker data set with different values of the parameter \(N_{\alpha}\), \(N_t\) and \(T\). We can see that the best values are: \(N_{\alpha}=12\), \(N_t=6\) and \(T=10\). The basic fragment length \(s_b\) should be approximately equal to the average stroke width of the input document. We have found the average stroke width of the whole Firemaker data set is approximately equal to 5. Therefore, we empirically set \(s_b = 5\).

4.1.3. Performance of writer identification based on single-script

In this section, we evaluate the feature performance for writer identification based on single-script and the results on five data sets are given in Table 1, from which we can see that the textural-based features provide better results than the grapheme-based features. The results of CoLBP are better than LBP. LBPrms provides better results on the five data sets than LBP and RLH, except ICFHR2012 with Arabic handwriting. CoHinge and QuadHinge give the better results than Hinge on all the five data sets. These results demonstrate that the joint feature distribution followed by the JFD principle can improve the performance of writer identification.

We can also find that none of these features achieve the best results on all the five data sets. The QuadHinge feature achieves the best
The writer identification performance based on single-script on five data sets: Firemaker, IAM, CERUG, ICFHR2012 and ICDAR2013. The column “Dim” is the dimensionality of each feature.

<table>
<thead>
<tr>
<th>Feature</th>
<th>CERUG-MIXED</th>
<th>CERUG-Synthetic</th>
<th>ICDAR2013-Synthetic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Top-1</td>
<td>Top-10</td>
<td>Top-1</td>
<td>Top-10</td>
</tr>
<tr>
<td>LBP</td>
<td>70.9</td>
<td>91.9</td>
<td>33.3</td>
</tr>
<tr>
<td>CoLBP</td>
<td>82.4</td>
<td>97.6</td>
<td>61.4</td>
</tr>
<tr>
<td>RLH</td>
<td>47.1</td>
<td>82.8</td>
<td>83.3</td>
</tr>
<tr>
<td>LBPruns</td>
<td>91.0</td>
<td>97.1</td>
<td>106.4</td>
</tr>
<tr>
<td>Hinge</td>
<td>85.2</td>
<td>95.7</td>
<td>84.3</td>
</tr>
<tr>
<td>CoHinge</td>
<td>96.7</td>
<td>98.6</td>
<td>89.5</td>
</tr>
<tr>
<td>$\Delta$Hinge</td>
<td>88.6</td>
<td>99.5</td>
<td>88.1</td>
</tr>
<tr>
<td>TCC</td>
<td>92.9</td>
<td>96.7</td>
<td>84.2</td>
</tr>
<tr>
<td>QuadHinge</td>
<td>93.8</td>
<td>97.6</td>
<td>91.4</td>
</tr>
<tr>
<td>Quill</td>
<td>75.2</td>
<td>90.9</td>
<td>73.3</td>
</tr>
<tr>
<td>QuillHinge</td>
<td>85.2</td>
<td>98.1</td>
<td>94.8</td>
</tr>
<tr>
<td>COLD</td>
<td>93.8</td>
<td>100</td>
<td>93.3</td>
</tr>
<tr>
<td>CO³</td>
<td>56.2</td>
<td>89.5</td>
<td>89.0</td>
</tr>
<tr>
<td>IC</td>
<td>67.1</td>
<td>91.0</td>
<td>94.3</td>
</tr>
<tr>
<td>Junclets</td>
<td>91.4</td>
<td>100</td>
<td>95.7</td>
</tr>
<tr>
<td>kSF</td>
<td>84.8</td>
<td>97.1</td>
<td>94.7</td>
</tr>
<tr>
<td>IC</td>
<td>84.8</td>
<td>98.6</td>
<td>94.8</td>
</tr>
</tbody>
</table>

**Fig. 12.** Writer identification performance of the QuadHinge feature with different parameters (the number of curvature bins $N_c$, the number of angle bins $N_l$ and the value of maximal scales $T$) on the Firemaker data set.

The results on the Firemaker, IAM and CERUG with Chinese data sets, because the QuadHinge captures the curvature information of handwriting based on the writing angle and the curvature measure of the contour fragments with a multiple scale strategy. The QuillHinge feature provides the best results on CERUG with English and ICDAR2013 data sets because handwritten documents on these two data sets were written with different pens and the QuillHinge feature can capture the writing instrument property. However, the dimension of the QuillHinge is also high, which needs more computational time than other features. The second best performance is achieved by COLD on the CERUG data set with English handwriting because the English handwriting written by Chinese subjects contain less curvature [7] and the curvature-free COLD feature can capture this property. The best result on the ICFHR2012 data set is achieved by the CoHinge feature, and its performance is significantly better than other features.

For the grapheme-based features, the Junclets provides the best results on the Firemaker, IAM, CERUG and ICDAR2013 with English data sets. However, CO³ provides the best Top-1 result on the ICFHR2012 with Arabic data set and the IC feature gives the best result on the Greek handwriting of ICDAR2013 data set.

**4.1.4. Performance of writer identification based on mixed-scripts**

In this section, we evaluate the performance of writer identification based on mixed-scripts. To our best knowledge, the page 4 of the CERUG data set is the only real mixed-script data set, which is split into two parts for writer identification.
MIXED data set. We also create the synthetic mixed-scripts data set by merging two handwritten documents with different scripts from the same hand into one document. By this way, two synthetic mixed-scripts data sets can be generated: the CERUG-Synthetic data set which contains the synthetic handwritten documents with Chinese and English, and the ICDAR2013-Synthetic data set which contains the synthetic handwritten documents with English and Greek.

Table 2 shows the performance of different features on the three mixed-scripts data sets. The Top-1 performance of the LBP, CoLBP, LBPruns, CoHinge and COLD increases on the CERUG-MIXED data set and the performance of other features decreases compared to their performance on the single-script data set shown in Table 1. On the CERUG-Synthetic data set, only the RLH, LBPruns and COLD features provide better results among the textural-based features. The performance of all the grapheme-based features are improved on the CERUG-Synthetic data set and the performance of all of seventeen features are improved on the ICDAR2013-Synthetic data set. The main reason is that each document on the CERUG-Synthetic and ICDAR2013-Synthetic data sets contains more handwritten texts, which makes the code-book-based features more stable. The LBPruns, COLD and Junclets features reach 100% Top-10 recognition rates on the CERUG-MIXED data set and the IC and QuillHinge features reach 100% Top-10 rate on the ICDAR2015-Synthetic data set.

Another interesting observation can be found that only the LBPruns and COLD features improve the performance on the three mixed data sets. The reason might be that the LBPruns and COLD features are the curvature-free features which can handle the different scripts from the same hand. By this way, two synthetic mixed-scripts data sets can be generated: the CERUG-Synthetic data set which contains the synthetic handwritten documents with Chinese and English, and the ICDAR2013-Synthetic data set which contains the synthetic handwritten documents with English and Greek.

4.1.5. Performance of writer identification on a large mixed data set

In this section, we give the performance of the seventeen features on a large and mixed data set. Following the work [2], we merge the Firemaker, IAM, CERUG, CVL, ICFHR2012 and ICDAR2013 data sets to obtain a large and combined data set which contains 5177 handwritten documents from 1760 hands with six languages: Dutch, English, Chinese, German, Arabic and Greek. We call this data set as “Large Multi-script Handwritten Set” in the following sections.

Table 3 shows the performance of the different features on this large set. The CoHinge feature achieves the best results and Top-1 recognition rate is 93.8%. The QuadHinge feature also provides a comparable result with 92.2%, which is better than the QuillHinge feature. This indicates that the handwriting styles captured by CoHinge and QuadHinge take more important information than the property of writing instruments captured by the Quill and QuillHinge features on this large data set where handwritten documents are written with different pens and scripts. For the grapheme-based features, the performance of the Junclets and IC are comparable, which outperform other three methods.

The results of the feature combinations between textural-based and grapheme-based features are presented in Table 4. Generally, combining two features provide an improvement for writer identification [2,26]. However, from Table 4 we can see that combining CoHinge and QuadHinge with other grapheme-based features provides a worse performance, which demonstrates that the CoHinge and QuadHinge contain the discriminative information of handwriting style and linearly combining them with other grapheme-based features cannot introduce more useful information.

4.1.6. Performance of writer retrieval

In this section, we perform the task of writer retrieval based on the Large Multi-script Handwritten Set. The recognition rates in bold increase while with italic type decrease, compared to the best performance of the individual features (shown in Table 3) involved in the combination.

Table 4 shows the performance of different features on this large set. The CoHinge feature achieves the best results and Top-1 recognition rate is 93.8%. The QuadHinge feature also provides a comparable result with 92.2%, which is better than the QuillHinge feature. This indicates that the handwriting styles captured by CoHinge and QuadHinge take more important information than the property of writing instruments captured by the Quill and QuillHinge features on this large data set where handwritten documents are written with different pens and scripts. For the grapheme-based features, the performance of the Junclets and IC are comparable, which outperform other three methods.

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4.1.6. Performance of writer retrieval

In this section, we perform the task of writer retrieval based on the Large Multi-script Handwritten Set. The recognition rates in bold increase while with italic type decrease, compared to the best performance of the individual features (shown in Table 3) involved in the combination.

Table 5 The number of query samples with different text lines on the CERUG and CVL data sets for writer retrieval.

<table>
<thead>
<tr>
<th>Data set</th>
<th>line 1</th>
<th>line 2</th>
<th>line 3</th>
<th>line 4</th>
<th>line 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>CERUG</td>
<td>201</td>
<td>2095</td>
<td>1012</td>
<td>617</td>
<td>450</td>
</tr>
<tr>
<td>Chinese</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CVL</td>
<td>10,820</td>
<td>5038</td>
<td>3187</td>
<td>2118</td>
<td>2118</td>
</tr>
<tr>
<td>English</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
handwritten documents with different text lines, similar as our work [25]. We segment the handwritten document into text lines and conduct experiments on handwritten documents with different numbers of text lines from one to five for writer retrieval. We use the CVL data set [37], which contains handwritten documents from 310 writers, 27 of which wrote 7 texts and 283 writers have 5 texts. In this experiment, only English handwriting from 310 writers are considered. In addition, we also evaluate the performance of writer retrieval on the Chinese handwriting from the CERUG data set. Table 5 shows the number of query samples on the two data sets with different text lines.

We use the mean Average Precision (mAP) to measure the performance of writer retrieval, which is defined as:

\[ \text{mAP} = \frac{1}{N} \sum_{q=1}^{N} \text{AveP}(q) \]  

(14)

where \( N \) is the number query samples and \( \text{AveP}(q) \) is the average precision of the query \( q \).

Fig. 13 shows the results on the two CERUG Chinese and CVL English data sets. The performance is improved when the number of lines increases. All of the features give the reasonable results on the handwritten documents with at least three lines. The results of the CoHinge and QuadHinge features provide the best performance than other features on the two data sets and the performance of the Junclets feature is higher than other four grapheme-based features.

4.2. Script identification

Script identification is the problem to automatically recognize the script of a given document [38], and it has been widely studied on printed documents [39–42] and on handwritten documents [43,44]. Identifying script on handwritten documents is more difficult because handwritten texts contain not only the script shape information, but also handwriting styles from different writers. In this section, we evaluate the seventeen features for script identification. Furthermore, we investigate the relationship of feature performance between writer identification and script identification based on the Large Multi-script Handwritten Set, which is mentioned in the previous section. There are four major different scripts: Chinese, Arabic, Greek and Western scripts (including English, German and Dutch) and Fig. 14 gives an example handwriting of the four different scripts.

Fig. 15 shows the script identification performance with respect to the number of K using the K nearest neighbor (KNN) method. From the figure we can see that the results of all the features decrease slightly when \( K \) increases from 5 to 50. The best performance is achieved by the kCF and QuadHinge feature when \( K=10 \), which demonstrates that the character shapes take an important role for script identification (a similar observation has also been shown in [44]).

We also study the feature performance for both writer and script identification. Fig. 16 shows the relationship of feature performance of script identification with \( K=10 \) and the Top-10 performance of writer identification. From the figure we can see that QuadHinge is more closed to the top-right corner, which means that the QuadHinge feature is discriminative both for script identification and writer identification.

4.3. Historical manuscript dating

Historical manuscript dating has been studied recently in [45–51], which is the problem of automatically determining the date information of historical documents based on their handwriting styles and provides an efficient tool for historians or paleographers. The main challenge is how to extract the evolution of handwriting styles over time. In this section, we provide the performance of different features which could capture the handwriting style on the historical manuscript dating problem on the Medieval Paleographical Scale (MPS) data set [30, 51–53]. The MPS data set consists of 2858 images of charters produced between 1300 and 1550 CE in four corners of old Dutch language area: Arnhem, Leiden, Leuven and Groningen. Fig. 17 shows the time line of the MPS data set.

4.3.1. Evaluation criterion

For the dating problem, two measurements are widely used to measure the performance: the Mean Absolute Error (MAE) and Cumulative Score (CS) [54], which are defined as:

\[
\begin{align*}
\text{MAE} & = \sum_{i=1}^{N} |K(y_i) - K(y)|/N \\
\text{CS}(\alpha) & = N_{\leq \alpha}/N \times 100%
\end{align*}
\]  

(15)

where \( K(y_i) \) is the ground-truth of the input query document \( y_i \) and \( K(y_j) \) is the corresponding estimated key year, \( \leq \) is the absolute operator, \( N \) is the number of query documents and \( N_{\leq \alpha} \) is the number of test images on which the key year estimation \( K(y_j) \) makes an absolute error \( e = |K(y_j) - K(y_i)| \) no higher than the acceptable error level: \( \alpha \) years. For historians or paleographers, an error of \( \alpha = 25 \) is, more often than not, acceptable when dating the medieval historical documents on the MPS data set. Therefore, the error level \( \alpha \) is set to 25 years in this section.

1 The MPS data set has been collected by Petros Samara and Prof. Jan Burgers who study paleography.

2 The project website is: http://application02.target.rug.nl/monk/Projects/MPS/
4.3.2. Dating by writer identity

The writers of 1127 documents are labeled, produced by 143 writers with at least two samples on the MPS data set formed the MPS-Writer Known with Multiple samples (MPS-WKM) subset, and the writers of 899 documents are unknown, formed the MPS-Writer Unknown (MPS-WU) subset. Following our previous work [30], we perform the writer identification on the MPS-WKM set and perform the dating using the K nearest neighbors (KNN) method on the MPS-WU data set, considering the rest of documents as training samples, whose writers are known.

Table 6 shows the results of writer identification and dating by writer identity on the MPS data set with different features. From Table 6 we can see that the CoHinge and QuadHinge provide the best results for writer identification and Junclets gives the best results among the grapheme-based features. For dating by KNN, the best performance is achieved by Junclets when $K \leq 10$ and by CO3 when $K > 10$. For each feature, the performance of dating decreases when $K$ increases. Among the textural-based features, CoHinge gives the best performance when $K = 5$ and QuadHinge provides the best results when $K > 5$. Fig. 18 shows the relationship of Top-10 performance of different features for writer identification and dating by KNN with $K = 10$ on the MPS data set. From the figure we can see that the CoHinge and QuadHinge features are discriminative both for writer identification and dating.

4.3.3. Dating by general handwriting style classification

In this section, we conduct historical manuscript dating by general handwriting style classification, in which all documents from each key year are considered as a class (there is an obvious border between nearby key years in the MPS data set) and a linear Support Vector Machine (SVM) is trained to predict the date information, following the work [30,55]. All the documents on the MPS data set are randomly divided into two parts: a training set (70%) and a testing set (30%). The experiments are repeated 20 times and the average results with standard deviations are reported in this section.

Two different evaluation scenarios are considered, depending on whether including the writer duplicates on the training and testing data sets [50]:

1. wr.excl. scenario: documents from the same writer are carefully
selected and they should be only in the training or testing sets, never appear in both training and testing sets.

2. *wr.incl.* scenario: documents are randomly splitting into training and testing sets, without the consideration of the writer labels.

Table 7 shows the results of different features on the MPS data set. The best three results are achieved by CoHinge, QuadHinge and Junclets, which are much better than the Hinge and Quill features. Table 8 gives the performance of the feature combination between the texture-based and grapheme-based features. We can observe that the performance of feature combination is not necessarily better than the best result of the individual features involved in the combination. For the informative Junclets feature, only combining with Hinge, CoHinge and TCC gives an improvement in the scenario of the informative Junclets feature, only combining with Hinge, CoHinge best result of the individual features involved in the combination. For the performance of feature combination is not necessarily better than the texture-based and grapheme-based features. We can observe that the result, except the ΔHinge feature, is comparable, which are better other features, except LBP.

4.4. Manuscript localization

In this section, we conduct the experiments of historical manuscript localization based on the MPS data set, where historical manuscripts are from four cities: Arnhem, Leiden, Leuven and Groningen. The KNN and linear SVM are used to evaluate the performance of different features for manuscript localization.

Fig. 19 presents the results of different features with respect to the number of K using the KNN method. The best result is achieved by the LBP feature and the performance of the CoHinge and QuadHinge features are comparable, which are better other features, except LBP. Fig. 20 shows the performance using the linear SVM classification. The QuadHinge reaches the recognition rate 94.0% and CoHinge reaches 92.8%, which are higher than other features, as well as their performance when using the KNN method.
From the experimental results we can obtain the conclusions that:

1. the co-occurrence features are powerful than their original features for writer identification. For example, CoLBP provides better results than LBP and LBPruns gives better results than LBP and Run-lengths;
2. the proposed CoHinge and QuadHinge features provide the best results for writer identification on five data sets. The CoHinge and QuadHinge features are so discriminative that combining them with other grapheme-based features cannot provide an improvement; (3) the best results of script identification are given by the contour fragments and the QuadHinge features, because they can capture the character shape information, which takes an important role for script identification. The QuadHinge feature obtains the best results when doing the writer and script identification simultaneously; (4) the CoHinge, Junclets and QuadHinge are more powerful for historical manuscript dating and localization. However, LBP obtains the best performance for manuscript dating using the KNN method. From the experimental results, we can conclude that our novel QuadHinge and CoHinge features present the promising results for the four problems: writer and script identification, historical document dating and localization. In future work, more kernel functions could be investigated to achieve more powerful, as well as transform-invariant features.

### Acknowledgments

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