Delta-n Hinge: rotation-invariant features for writer identification

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***Abstract*—This paper presents a method for extracting rotation-invariant features from images of handwriting samples that can be used to perform writer identification. The proposed features are based on the Hinge feature [1], but incorporating the derivative between several points along the ink contours. Finally, we concatenate the proposed features into one feature vector to characterize the writing styles of the given handwritten text. The proposed method has been evaluated using Firemaker and IAM datasets in writer identification, showing promising performance gains.**

I. INTRODUCTION

Writer identification based on scanned handwriting is a useful behavioral biometric modality. It has extensive applications in forensic and historical document analysis. The hypothesis behind writer identification is that people have their own writing style which can be characterized based on the information present in their handwritten patterns [1], [2], [3], [4]. According to this basic hypothesis, a writer identification system based on a machine should consist of two main parts: representation of the writer shape information and the computation of similarity. Generally speaking, the measure of similarity is largely dependent on the feature representation of the writing styles. Therefore, the core task of designing a writer identification system is to design an effective and discriminative feature.

Writer identification is a hard problem which attracts scientific research in the area of pattern recognition. Over the recent years, a wide variety of methods are proposed in the literature. Based on the context of the features they used, the systems of writer identification are traditionally divided into two broad categories: text-dependent and text-independent methods [1], [2], [3], [4]. Text-dependent methods focus on the text content, while text-independent methods study some statistical features extracted from the entire image of a text block [5]. The proposed approach in this paper falls in the text-independent class, due to the fact that features are designed and extracted from the entire document images for writer identification.

Automatic writer identification can also be categorized into two groups: on-line and off-line methods [2] according to the type of documents they used. On-line (tablet based) recordings contain temporal information such that the velocity of the pen movements.The additional temporal information is useful both in writer identification and handwriting recognition [6]. Although the feature method that will be proposed in this paper is used in off-line document classification, it is easily extended to on-line writer identification, which is one of the noticeable advantages.

As mentioned above, the representation of writing style takes an important role in writer identification. Although the existing features have achieved high accuracy based on carefully scanned documents, to our best knowledge, none of them has been reported to be rotation-invariant. However, a small rotation angle can be easily introduced into the images of handwriting samples. In the real-world, poor scanning practices result in a small rotation angle, which may have a serious impact on the performance of writer identification system based on the rotation-variant features. To overcome this problem, this paper introduces rotation-invariant features for writer identification.

We present new features for off-line and text-independent identification of handwriting, which has several advantages: 1) The proposed features are rotation-invariant, which are, to our best knowledge, the first rotation-invariant features in identification of writers; 2) Although the proposed features are computed from offline documents, they are indicative of temporal events. There is a lawful relation between curvature and pentip velocity that has been extensively studied [7], [8], [9], [10]. The features proposed here, therefore, are also directly applied to on-line handwriting.

II. RELATED WORK

In previous studies, a wide variety of features have been proposed that serve to distinguish the writing of individual persons. There are two main types of features reported in the literature: codebook-based and contour-based features.

Codebook-based features are widely used in writer identification system. Schomaker et.al. has proposed to build a codebook using fragmented connected-component contours(FCO^3) [1], [12], [11]. Based on their methods, Ghiasi et al. used curve fragment and line fragment code extraction methods to build the codebook [13]. Code patterns in small windows are used to train the codebook in [3], which works on a much smaller scale of writing shapes. After construction of the codebook, a probability density functions(PDF) for handwriting can be computed based on the codebook and agglomerated in a histogram.

For high quality images, the edge-based or contour-based features have shown more effective performance in writer

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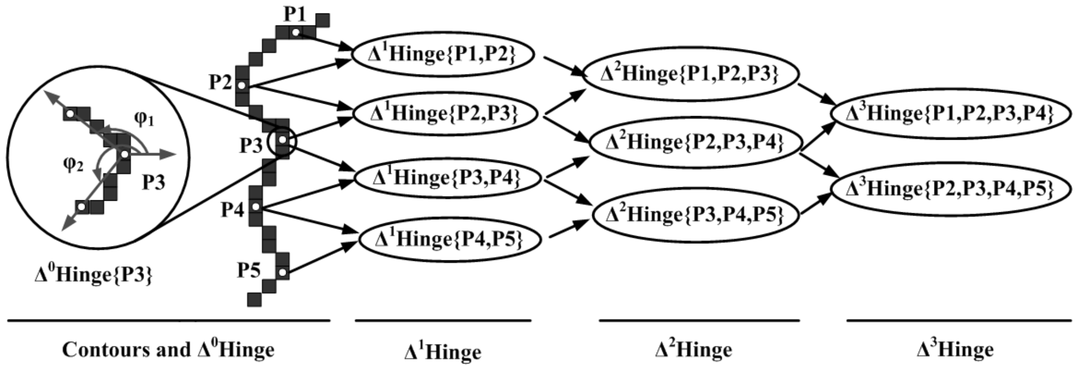

Fig. 1. Schematic description for the $\Delta^0 Hinge$, which is the original Hinge [11], $\Delta^1 Hinge$,$\Delta^2 Hinge$ and $\Delta^3 Hinge$, on the left in a piece of a contour with the points $P1, P2, P3, P4, P5$. The proposed method consists of computing angular difference in steps, increasing the order n of the $\Delta^n Hinge$.

identification [3], [14], than the codebook (fraglets) approach, but combining both methods is beneficial, especially in variable quality images. The contour-based feature are assumed to represent biometrical aspect rather than trained copybook character shapes [15]. The best contour-based features reported in the literature are the *Hinge* [1] and *Quill-Hinge* [4] features.

The *Hinge* feature was designed to capture the curvature of the ink trace of the document images, which is considered to be very discriminatory between different writers [1], [3]. The core idea is to consider two contour fragments together attached at a common end pixel and compute the joint probability distribution of the orientations of the two legs of the obtained "contour-hinge". The *Quill-Hinge* feature [4] is the combination of the *Quill* feature and *Hinge* feature. It is a probability distribution of the relation between the ink direction and the ink width. Therefore, its performance on the handwriting using different instruments is higher than others.

In this paper, we proposed a new set of features called $\Delta^n Hinge$ based on *Hinge* feature. Although the *Hinge* feature has been successfully used in some applications, such as Groningen Intelligent Writer Identification System(*GIWIS*) [16], there is an obvious drawback: it is sensitive to the rotation of the documents. To overcome this problem, we generalize the *Hinge* to $\Delta^n Hinge$ features, which have the rotation-invariant property when $n = 1, 2, 3....$ On the other hand, when $n = 0$, $\Delta^0 Hinge$ is exactly the *Hinge* feature. Therefore, the proposed $\Delta^n Hinge$ features can be considered as the generalization of the *Hinge*, and contain more information.

III. Δ^nHINGE FEATURE

The *Hinge* feature captures the joint probability distribution of the orientations of two legs of the obtained "contour-hinge" [1] along the ink contours. Given an arbitrary starting point, a counter-clockwise evaluation follows. If we assume that the points on the contour are generated one by one, like the on-line handwriting, with a writing direction φ, the two legs of the hinge can be defined as "previous" orientation φ_1, which is the opposite to the writing direction φ, and as "succeeding" orientation φ_2, which follows the writing direction φ. Here we denote one point p_j associated with two orientations $\varphi_1\{p_j\}$ and $\varphi_2\{p_j\}$ as a "Hinge kernel"(see $\Delta^0 Hinge\{p_3\}$ in Figure 1).

The Hinge feature can be considered as a statistical descriptor of the contours, which acount the probability of each pattern appeared in the contours. For each point p_j which has pair angles($\varphi_1\{p_j\}, \varphi_2\{p_j\}$), the probability of such pattern in a given document is calculated by:

$$p(\varphi_1, \varphi_2) = \frac{c_{(\varphi_1,\varphi_2)}}{C} \tag{1}$$

Here, φ_1 and φ_2 means the possible value of the two orientations in all points along the ink contours. $c_{(\varphi_1,\varphi_2)}$ is the number of the pattern (φ_1, φ_2) appeared in the given document image, and C is the total number of points in all the ink contours of the document image. $p(\varphi_1, \varphi_2)$ is a bivariate probability distribution capturing both the orientation and the curvature of contours [1]. Finally, the probability distribution is agglomerated in a $q \times q$ histogram, where q is the number of angle bins. The histogram was built using bilinear interpolation to avoid distortions caused by measures close to bin boundaries.

In this paper, we propose a new set of features based on the *Hinge* feature for writer identification, which is called $\Delta^n Hinge$. A sequence of pixels with fixed interval of distance along the ink contours are considered simultaneously to construct the probability of angle derivative on the "previous" and "succeeding" directions. We denote such sequence with fixed interval of Manhattan distance Δl as $\{p_j, p_{j+1}, ..., p_{j+n-1}\}$, where $\Delta l = |p_i - p_{i-1}|, i = j + 1, j + 2, ..., j + n - 1$. The starting point of the sequence is p_j, and the end point is $p_j + n - 1$. Given this sequence, the $n-1$ derivative of the two orientations in Hinge kernel is denoted as:

$$\begin{aligned} {}_j\Delta^{n-1}\varphi_i = \varphi_i\{p_j, p_{j+1}, p_{j+2}, ..., p_{j+n-1}\} \\ i = 1, 2 \end{aligned} \tag{2}$$

Here, φ_1 and φ_2 are the two "previous" and "succeeding" orientations in Hinge kernel respectively. ${}_j\Delta^{n-1}\varphi_i$ is the $n-1$ derivation along the φ_i orientation with starting point p_j.

When the $n - 1$ derivative of the two orientations is obtained, the n derivative is computed as:

$$ {}_j\Delta^n\varphi_i = \frac{{}_{j+1}\Delta^{n-1}\varphi_i - {}_j\,\Delta^{n-1}\varphi_i}{\Delta l} \quad i = 1, 2 \tag{3} $$

There are two sequences with different stating points p_{j+1} and p_j subjected to $|p_{j+1} - p_j| = \Delta l$ are involved in the computation of n derivation in two orientations of the Hinge kernel. From Eq(3), we can find that the computation of n derivative relies on the $n-1$ derivative. From Eq(2), when $n - 1 = 0$, we can get the initial value of "previous" angle ${}_j\Delta^0\varphi_1 = \varphi_1\{p_j\}$ and "succeeding" angle ${}_j\Delta^0\varphi_2 = \varphi_2\{p_j\}$, which are the Hinge kernel on point p_j (see $\Delta^0 Hinge$ on point p_3 in Figure 1).

Given handwritten contours, each pixel on the contour is considered as the jth start point and the pattern $({}_j\Delta^n\varphi_1, {}_j\,\Delta^n\varphi_2)$ is obtained by Eq(3). All the patterns are quantized into a histogram, and finally the $\Delta^n Hinge$ feature is given by:

$$ \begin{aligned} \Delta^n Hinge &= p(\Delta^n\varphi_1, \Delta^n\varphi_2) \\ n &= 0, 1, 2, 3, ... \end{aligned} \tag{4} $$

Here, the $p(\Delta^n\varphi_1, \Delta^n\varphi_2)$ is defined as same way as Eq(1). From the Eq(2), Eq(3) and Eq(4), we can find that the $\Delta^n Hinge$ feature is built on $\Delta^{n-1} Hinge$, which can be recursively computed by $\Delta^{n-2} Hinge$ and $\Delta^{n-3} Hinge$ and so on. The initial $\Delta^0 Hinge$ is the *Hinge* [1]. Therefore, the proposed $\Delta^n Hinge$ is the generalization of the *Hinge* feature, and the *Hinge* feature is the special case of the Δ^nHinge feature when $n = 0$.

Corollary 1: Properties of $\Delta^n Hinge$ feature:

(1) When $n = 0$, the $\Delta^0 Hinge$ is the $Hinge$ feature [1].

(2) When $n = 1$, the $\Delta^1 Hinge$ works similarly as the first derivative(alike to the angular velocity long the contours) of the pen coordinates in signature verification [17], [18].

(3) When $n = 2$, the $\Delta^2 Hinge$ works similarly as the second derivative(alike to accelerations) of the pen coordinates in signature verification [17], [18].

(4) When $n > 2$, the $\Delta^n Hinge$ contains high order derivative information of the contours in the document images.

Corollary 2: The proposed $\Delta^n Hinge$ has the rotation-invariant property when $n > 0$. Assume that the document has a small rotation angle ϕ, and the probability of the rotated document is denoted as $p(\widetilde{\Delta^n\varphi_1}, \widetilde{\Delta^n\varphi_2})$. Then we have

$$ \begin{aligned} p(\widetilde{\Delta^n\varphi_1}, \widetilde{\Delta^n\varphi_2}) &= p(\Delta^n\varphi_1, \Delta^n\varphi_2) \\ n &= 1, 2, 3, ... \end{aligned} \tag{5} $$

Proof: According to Eq(3), if there is a small rotation angle ϕ on the whole document, when $n > 0$, the n derivative of the Hinge kernel is computed as:

$$ \begin{aligned} {}_j\widetilde{\Delta^n}\varphi_i &= \frac{({}_j\Delta^{n-1}\varphi_i + \phi) - ({}_{j+1}\Delta^{n-1}\varphi_i + \phi)}{\Delta l} \\ &= \frac{{}_j\Delta^{n-1}\varphi_i - {}_{j+1}\,\Delta^{n-1}\varphi_i}{\Delta l} = {}_j\,\Delta^n\varphi_i \\ i &= 1, 2; \quad n = 1, 2, 3, ... \end{aligned} \tag{6} $$

We can conclude that the probability distribution is not changed after rotation.

A. Ho^2D^n feature

Previous studies have shown that the performance of combined different feature sets is better than individual features [11], [3], [1], [5]. Inspired by this observation, the different components of the proposed $\Delta^n Hinge$ feature are concatenated into one feature vector to form the **Histograms of Hinge over Derivative with** n, dubbed $HoHoD^n$,or Ho^2D^n, which is defined as:

$$ Ho^2D^n = \{\Delta^0 Hinge, \Delta^1 Hinge, ..., \Delta^n Hinge\} \tag{7} $$

From this definition, the Ho^2D^0 is the *Hinge* probability feature, which is sensitive to rotation. If the rotation-invariant feature is required, the $\Delta^0 Hinge$ should be excluded from Ho^2D^n, here we denote as Ho^2D^{n+}, which is a rotation-invariant feature.

IV. Writer Identification

A. Dissimilarity measure

The proposed features belong to the class of probability distribution functions(PDF) features, For which special distance function exist in [1], [3]. The χ^2 was found to perform best. Thus the experimental results reported in the subsequent sections will be based on χ^2 distance.

B. Writer identification

Nearest-neighbor classification with a "leave-one-out" strategy is often used in writer identification system [11], [1], [3], [4]. Given a query document Q, the system will sort all the documents in the train set based on the distance to the query Q. Ideally, the sample with the minimum distance should be the pair produced by same writer. Not only the nearest neighbor(Top-1), but also a longer list up to a given rank(Top-10) are used to measure the performance of the identification system. In our experiments, we also use the nearest-neighbor method with the "leave-one-out" strategy to perform writer identification, and use the identification rate of both Top-1 and Top-10 to evaluate our method.

V. Experiments

A. Datasets

In this paper, two dataset are used to test our method: Firemaker [19] and IAM [20]. The Firemaker set contains handwriting collected from 250 Dutch subjects, who were required to write four different A4 pages. In this dataset, lowercase pages are commonly used to test writer identification methods [11], [1]. In our experiments reported in this paper, we performed searches/matches of page 1 versus page 4 (lowercase pages). We modified the IAM dataset as [1]: We selected randomly two documents for those writers who contributed more than two documents, and we have split the document roughly in half for those writers with a unique page. Finally, the dataset from IAM used in the experiments contains lowercase handwriting from 650 people, two samples per writer.

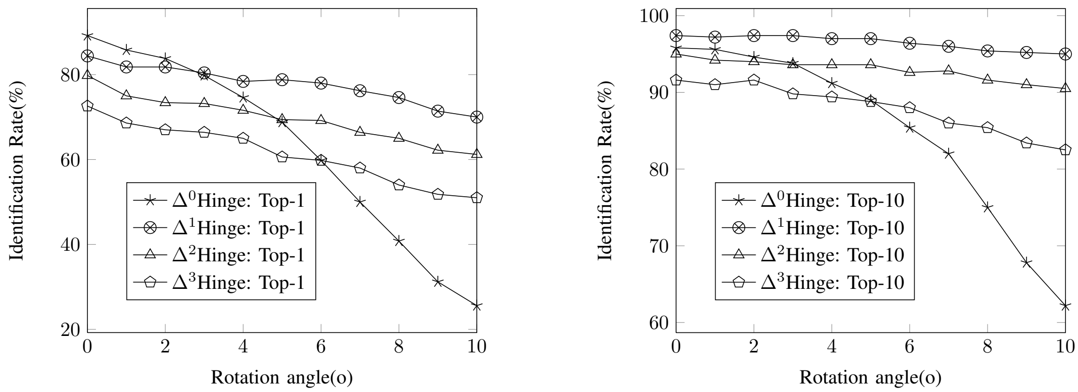

Fig. 2. Rotation study on firemaker dataset. The left figure shows the top rank, i.e.(Top-1) identification rate with rotation angle (o), and the right one shows the Top-10 performances

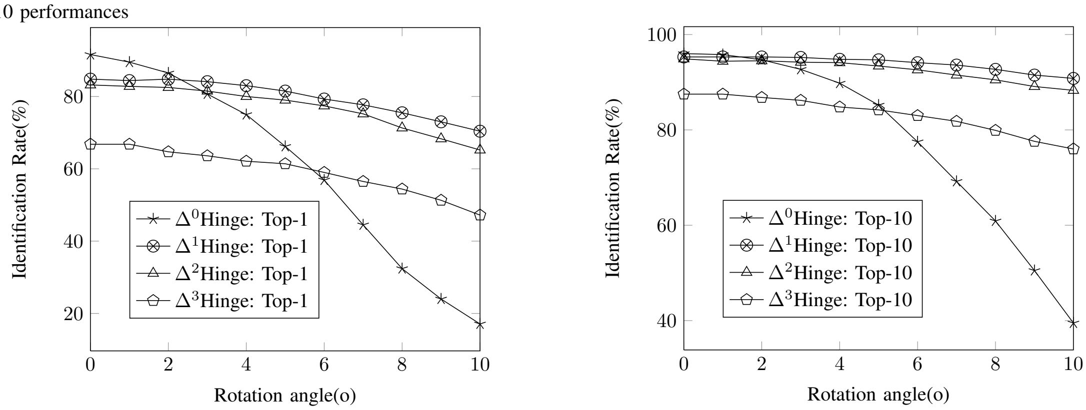

Fig. 3. Rotation study on IAM dataset. The left figure shows the Top-1 identification rate with rotation angle (o), and the right one shows the Top-10 performances. Note that the Firemaker data set is based on a single type of ball point pen, whereas the IAM data set contains many writing instruments.

TABLE I. PERFORMANCE OF $\Delta^n Hinge$ FEATURES

$\Delta^n Hinge$	n	0	1	2	3	4	5	6	7	8	9	10
Firemaker [19]	Top-1	**89.2**	84.4	79.8	72.6	75.0	60.2	65.0	57.6	57.0	45.6	40.1
	Top-10	95.8	**97.4**	95.0	91.6	93.4	84.6	86.8	85.0	86.2	73.8	70.5
IAM [20]	Top-1	**91.6**	84.8	83.5	66.8	67.3	49.9	50.8	38.6	43.0	30.3	35.5
	Top-10	**96.0**	95.3	94.9	87.5	87.2	76.6	78.2	66.7	71.9	58.5	63.4

B. Experimental setting

The images of the Firemaker and IAM datasets are binarized using Otsu thresholding [21], which is a widely used and efficiently computed binarization method. After thresholding, the ink contours are extracted by tracing method proposed in [4]. Given the ink contours, the two orientations φ_1 and φ_2 of Hinge kernel are computed at all pixels on those contours.

There are four parameters in the proposed method, number of angle bins q, leg length r, Manhattan distance Δl, and the number of derivative n. It was shown in [4] that the performance is insensitive to the value of q, as long as it is at least about 30, and to value of r as long as it is between 10 and 100. Therefore, in our experiment we set $q = 40, r = 15$. We experimentally set the Manhattan distance $\Delta l = 7$ and found that it works quite well. The experiment shows that the better choice for n is $n = 2$ or $n = 3$ which is dependent on the specifical dataset.

C. Rotation-invariant study

In this section, we perform a rotation-invariant study on the two datasets. In both datasets, one writer has two samples. Therefore, we keep the first one and rotate the second one with a small φ angle. In our experiment, we just evaluate the rotation angle $\varphi \preceq 10$. For those documents which have rotation angle greater than 10, some rotation operators can be used manually or automatically to adjust it to the normal ones. The results are presented in Figure 2 and Figure 3, on the Firemaker and IAM dataset respectively. The figures show that, with the increase of rotation angle from 0 to 10, the Top-1 performance of $\Delta^0 Hinge$ decrease significantly from 89.2%

to 25.6% in Firemaker, a drop of 63.6%, and from 91.6% to 17.1% in IAM, a drop of 74.5%. However, the performance of $\Delta^1 Hinge$, $\Delta^2 Hinge$ and $\Delta^3 Hinge$ decreases slightly, by 14.4%, 18.6% and 21.6% in Firemaker respectively, and by 4.5%, 6.6%, 11.5% in IAM respectively. The slight decrease is partly caused by quantization artifacts introduced by the rotation operator, since the image is defined on a discrete grid. The same trend can be found on the Top-10 performance on both Firemaker and IAM datasets. Therefore, the proposed $\Delta^n Hinge, n > 0$ are less sensitive to rotation.

D. Performance of $\Delta^n Hinge$ features

In this section, we evaluate the performance of each part of $\Delta^n Hinge$. Table I contains the achieved performances for both datasets, with different n from 0 to 10.

The performances are little different on the two datasets. For Firemaker, the maximum identification rate of Top-10 is achieved when $n = 1$. When $n > 1$, the identification rate is decreased gradually. However, the performance in IAM decreases gradually from $n = 0$. The main reason is that the documents in IAM are pen-dependent. The writer used different writing instruments to create the handwriting text, which may cause a variative in the derivative along the ink trace. We can conclude from the table that $\Delta^n Hinge$ contains less information with higher value of n. For example, when $n > 100$, the derivative of the two orientations will be closed to zero. Another interesting observation is that, although the performance of the features with different n varies in both two datasets, $\Delta^n Hinge$ contains discriminative information when $n \leq 3$.

E. Performance of Ho^2D^n feature

In this section, the performance of the proposed Ho^2D^n feature which concatenates the $\Delta^n Hinge$ is evaluated using the two datasets. The results are presented in Figure 4, where we can find that the maximum Top-1 identification rate is 90.4% in Firemaker when $n = 1$ and 97.2% in IAM when $n = 2$. The corresponding Top-10 identification rates are 98.2% ($n = 4$) in Firemaker and 97.2% ($n = 2$) in IAM dataset. The results support our conclusion we mentioned before that the $\Delta^n Hinge$ contains discriminative information when $1 \leq n \leq 4$.

F. Performance of Ho^2D^{n+} feature

In this section, the performance of the Ho^2D^{n+} is evaluated in both databases. The results are shown in table II. Without $\Delta^0 Hinge$ feature, the performance of Top-1 is down. However, the results of Top-10 are still comparable to Ho^2D^n features.

G. Comparison with other studies

In this section, we present a performance comparison of our method with some recent studies on writer identification. Table III and table IV show the performance of recent studies and ours in Firemaker and IAM datasets. The proposed feature performs better than others on Firemaker data set, which achieves 90.4%(Top-1).

TABLE II. PERFORMANCE OF Ho^2D^{n+} FEATURES

Ho^2D^{n+}	n	1	2	3
Firemaker [19]	Top-1	84.0	**84.0**	81.4
	Top-10	97.0	**97.4**	97.2
IAM [20]	Top-1	85.8	**86.4**	84.8
	Top-10	**96.0**	95.3	94.9

TABLE III. COMPARISON OF WRITER IDENTIFICATION STUDIES ON THE FIREMAKER DATABASE.

Study	Top1(%)	Top10(%)
Ghiasi and Safabakhsh [13]	89.2	98.6
Bulacu and Schomaker [1]	83.0	95.0
Brink and Smit [4]	86.0	97.0
Proposed	**90.4**	**98.2**

Comparing the performance on 650 writers of IAM data set, we achieve an identification rate of 93.2%(Top 1) and 97.2%(Top 10), which is better than the results in [1], [3], and comparable to the results in [13]. Note that Top-1 performance of *Quill-Hinge* [4] is higher on IAM data set due to the fact that *Quill-Hinge* feature is designed for pen-dependent documents.

TABLE IV. COMPARISON OF WRITER IDENTIFICATION STUDIES ON THE IAM DATABASE.

Study	Top1(%)	Top10(%)
Siddiqi and Vincent [3]	89.0	97.0
Ghiasi and Safabakhsh [13]	93.7	97.7
Bulacu and Schomaker [1]	89.0	97.0
Brink and Smit [4]	97.0	98.0
Proposed	**93.2**	**97.2**

H. Comparison with ICDAR2013 competition [22]

We evaluate the proposed method on ICDAR2013 database [22] which is used for writer identification competition. This database consists 250 writers with four documents per writer. Two documents were written in Greek, the other two in English. Ideally, the parameters in proposed method should be learned from this dataset. However, in this experiment, we just set Manhattan distance $\Delta l = 15$ and others is same as previous experiments. The results in table V shows that our proposed method is comparable to the state-of-the-art method in ICDAR2013 competition.

VI. CONCLUSION

We propose a new set of features which generalizes the Hinge method for writer identification in a rotation-invariant manner. The results on two widely used data sets and a comparison with the ICDAR2013 benchmark show that the proposed method is promising and comparable to the state-of-the-art techniques. The implication of this finding is that not only the (absolute) slant angle distribution of handwriting

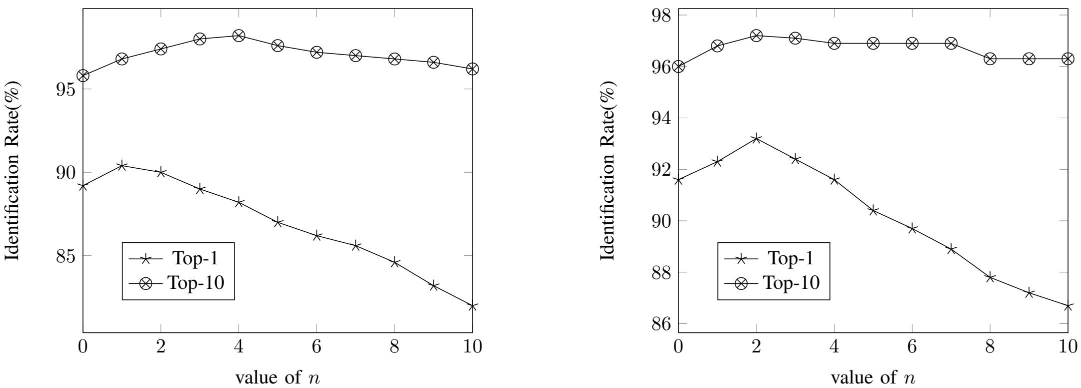

Fig. 4. Performance of different n of Ho^2D^n feature. The left figure is the performance on Firemaker dataset, and the right one is on IAM dataset.

TABLE V. COMPARISON OF WRITER IDENTIFICATION STUDIES WITH ICDAR2013 COMPETITION [22].

	method	Top-1	Top-10
Greek Dataset	state-of-the-art in ICDAR2013	95.6	99.2
	Proposed method	96.0	98.4
English Dataset	state-of-the-art in ICDAR2013	94.6	99.0
	Proposed method	93.4	97.8

is biometrically informative; also the distribution of relative angles along the trace provides writer-specific information, capturing the curvature of the patterns.

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