Offline Text-Independent Writer Identification Based on Scale Invariant Feature Transform

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***Abstract*— This paper proposes a novel offline text-independent writer identification method based on scale invariant feature transform (SIFT), composed of training, enrollment, and identification stages. In all stages, an isotropic LoG filter is first used to segment the handwriting image into word regions (WRs). Then, the SIFT descriptors (SDs) of WRs and the corresponding scales and orientations (SOs) are extracted. In the training stage, an SD codebook is constructed by clustering the SDs of training samples. In the enrollment stage, the SDs of the input handwriting are adopted to form an SD signature (SDS) by looking up the SD codebook and the SOs are utilized to generate a scale and orientation histogram (SOH). In the identification stage, the SDS and SOH of the input handwriting are extracted and matched with the enrolled ones for identification. Experimental results on six public data sets (including three English data sets, one Chinese data set, and two hybrid-language data sets) demonstrate that the proposed method outperforms the state-of-the-art algorithms.**

***Index Terms*— Offline text-independent writer identification, SIFT, word segmentation, SIFT descriptor signature, scale and orientation histogram.**

I. Introduction

AUTOMATIC offline text-independent writer identification is very important for forensic analysis, documents authorization, and calligraphic relics identification, etc. The offline text-independent writer identification is to determine the writer of a text among a number of known writers using their handwriting images. Extensive researches have been conducted in this field [1]–[7]. And a series of international writer identification contests [8]–[12] have been successfully organized. Plamondon et al. [13] presented a comprehensive survey of early research literatures with respect to automatic writer identification. In general, the existing approaches of offline text-independent writer identification can be roughly divided into two categories: texture-based approaches and structure-based approaches.

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Texture-based approaches take handwriting texts as a special texture image and extract the textural features for writer identification. Said et al [2], Zhu et al [14] and Hanusiak et al [15] used a grey-level co-occurrence matrix (GLCM) to extract the textual features from the handwriting images. He et al [6] extracted features based on hidden Markov tree (HMT) model in wavelet domain for writer identification. He et al [16] and Du et al [17] extracted wavelet-based textural feature from handwriting images. Helli et al [18] used Gabor and XGabor filter to extract features from handwriting data and employed a feature relation graph (FRG) to represent the extracted features. Bertolini et al [19] considered both local binary patterns (LBP) and local phase quantization (LPQ) as texture descriptors of handwritings for writer verification and identification.

Compared with the textural features, the structural features of handwriting are much more intuitionistic, notable and stable for writer identification. Therefore, recently a large number of the researches are focused on the structure-based approaches for writer identification. Most of the structure-based approaches extract features from the points on contours of handwritings. Bulacu et al [5] proposed several edge-based directional features of handwriting, i.e. edge-direction distribution, edge-hinge distribution and directional co-occurrence PDF to characterize the individuality of the writers. Maaten et al [20] introduced multi-scale analysis to the edge-hinge distribution and yielded a multi-scale edge-hinge feature. Li et al [21] proposed a grid microstructure feature (GMF) by using the edge pixel pairs for writer identification. Brink et al [22] extracted the width and direction of ink traces to form the Quill-Hinge feature. Siddiqi et al [23] extracted features from the chain code of handwriting contours for writer identification. Schomaker et al [3] and Ghiasi et al [24] employed the coordinates of the points on the normalized and resampled contours of the connected-components [3] (or segments [24]) to form feature vector for codebook generation and writer identification. Jain et al [25] and Ghiasi et al [24] used straight line segments to fit the connected-component contour of handwriting and extracted the features according to the relationship of these segments. Djeddi et al [26] extracted a set of run-length features on a binary image of handwriting. Instead of using points on contours, Bulacu et al [5] segmented the allograph (i.e. connected-component) into several fragments and then used the normalized fragment to generate the codebook and identify writers. Siddiqi et al [23] divided handwriting image into small fragments with a fixed window and then extracted codebook

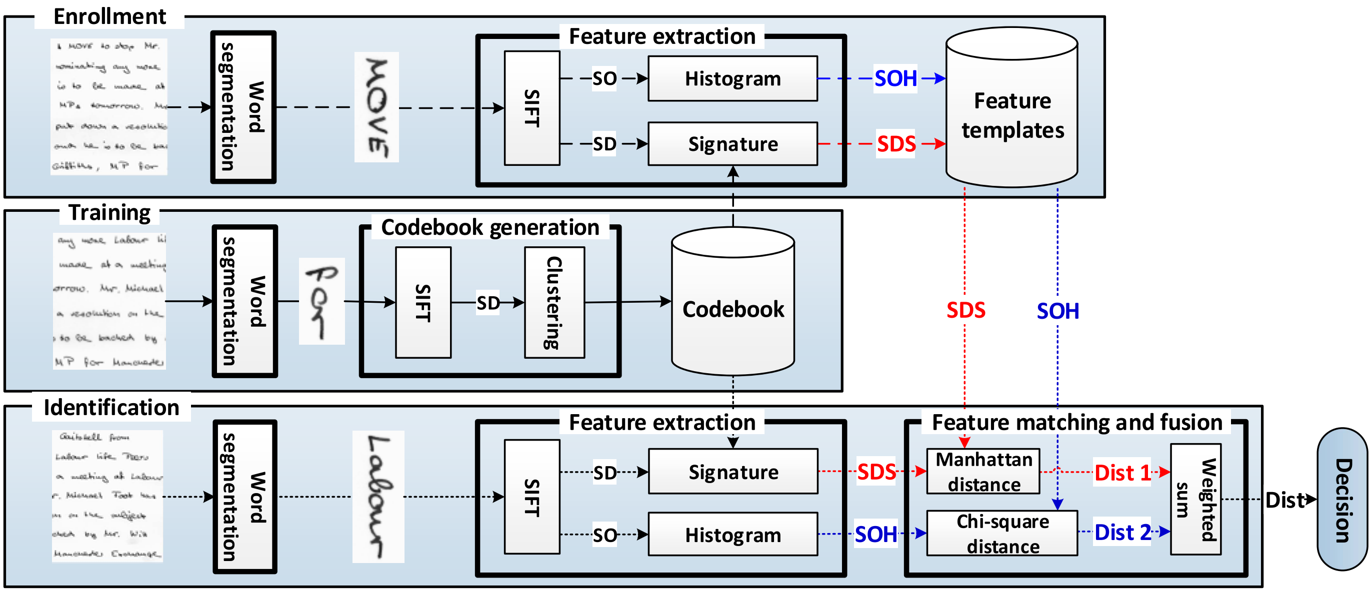


Fig. 1. The framework of the proposed method.

based features to represent different writers. Gordo et al [7] exploited the blurred shape model descriptor (BSM) to represent the structure of handwritten musical symbols for writer identification.

Most of the existing structure-based approaches are based on the contours or the allograph fragments of handwriting, which may be easily affected by the slant and aspect ratio of the characters in handwriting. Moreover, these approaches extract features from the allographs, which fail to extract the structural features between the allographs in the same words. However, when writing a document, the words are always taken as a whole and the structures of the whole word are stable and have a strong discriminability for different writers. Therefore, the structures between allographs in the same word are also important for characterizing writer's individuality. To deal with these problems, this paper proposes a scale invariant feature transform (SIFT) based method to extract the key point based structural features at word level from handwriting images, which contains the structural information of whole words and is insensitive to the aspect ratio and slant of the characters.

The rest of this paper is organized as follows: Section II gives a description of the proposed method in detail. Section III reports the experimental results and analyses. Finally, the conclusions are presented in Section IV.

II. Methodology

A. The Framework of the Proposed Method

The proposed method consists of three stages: training, enrollment, and identification, as shown in Fig. 1.

In all of these three stages, the handwriting image is firstly segmented into word regions (WRs). Then the SIFT is used to detect the key points and extract their SIFT descriptors (SDs), and the corresponding scales and orientations (SOs) from the WRs. The SDs and SOs will be used in different ways in different stages.

In the training stage, SDs extracted from the training dataset are used to generate a codebook for the use of enrollment and identification.

In the enrollment stage, two features, called SD signature (SDS) and SO histogram (SOH), are extracted from SDs and SOs of WRs of the enrolling handwriting image and stored for identification.

In the identification stage, the SDS and SOH are extracted from the input handwriting images and respectively matched with the enrolled ones to get two matching distances, which are then fused to form the final matching distance for decision.

As shown in Fig. 1, there are four main parts in the framework, i.e. word segmentation, codebook generation, feature extraction, and feature matching and fusion.

B. Word Segmentation

To extract the word-level structural features of handwriting image, we should segment the handwriting image into word regions (WRs). Word segmentation is very important for handwriting image analysis. In early literatures, handwriting images are manually segmented [27], which is very time-consuming and tedious. Many automatic word segmentation techniques have been devised in recent years, most of which are based on text line segmentation. Louloudis et al [28] firstly segmented text lines by using Hough transform, and then segment words from each text line according to the distances between the adjacent connected components in vertical project domain. Papavassiliou et al [29] segmented text lines based on a sequence of consecutive non-overlapped vertical zones and located words by adopting an SVM-based metric in each text line. These text line segmentation based techniques may fail to segment some skew handwriting images, in which the text lines are not horizontal and hence may not be easily

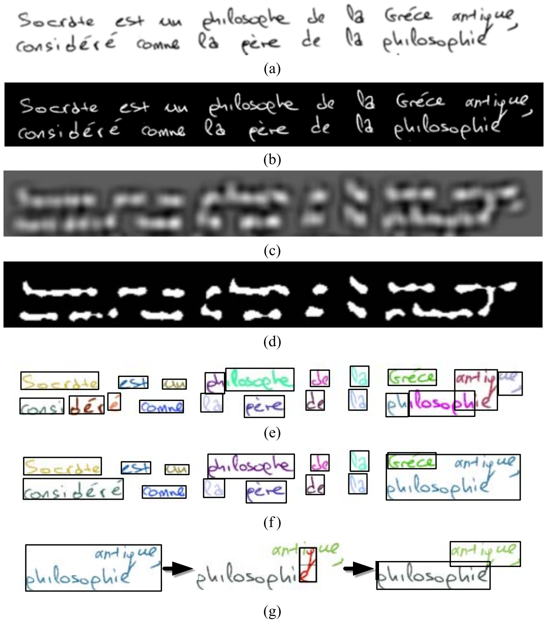


Fig. 2. Word segmentation process. (a) Original image (I). (b) Binary image (I_b). (c) Filtered image (I_f). (d) Binary image (I_{fb}). (e) Semi-word regions (SWRs). (f) Merged image (WRs). (g) Splitting overlapping CC.

segmented. To avoid text line segmentation and reduce the effect of the direction of text lines, in this work, an isotropic LoG filter is employed to segment words from handwriting images.

Given a handwriting image I, as shown in Fig. 2(a). The word segmentation process can be simply described as below.

1. Converting I to a binary image I_b by using Otsu's algorithm [See Fig. 2(b)].
2. Getting all connected-components (CCs) in I_b and then computing their average height h_a.
3. Filtering I_b with an isotropic LoG filter to get the filtered image I_f [See Fig. 2(c)]. Since the space between the connected-components (CCs) of the samse word are much less than the space between different words, the LoG filter with a suitable variance can concatenate the CCs of same words and separate different words. Since the space between the CCs of same words is in direct ratio to the height of the words in a normal handwriting document, this work uses the average height h_a of all CCs in I_b to decide the variance σ of the filter as $\sigma = 2.5 \times h_a$.
4. Binarizing I_f to get a binary image I_{fb} by using the threshold obtained by Otsu's algorithm [See Fig. 2(d)].
5. Assigning each connected-component in I_b to the nearest connected region of I_{fb} to form semi-word regions (SWRs), which are labeled with different colors in Fig. 2(e).
6. Merging the SWRs to get the word regions (WRs) according to the distances between the adjacent SWRs [See Fig. 2(f)].
7. Splitting the overlapping connected-components (OCCs) which run along multiple text lines from the middle line of these OCCs' boundary box [See Fig. 2(g)].

After word segmentation, a handwriting document image is divided into many WRs, which will be used for feature extraction.

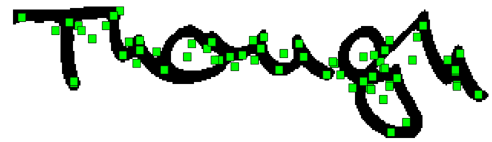


Fig. 3. The key points detected in a word region by SIFT.

C. SIFT

Scale invariant feature transform (SIFT), presented by Lowe [30] for distinctive scale-invariant features extraction from images, has been widely and successfully applied in many fields [31]. The SIFT algorithm has four major stages of computation: (1) scale-space construction, (2) key point localization, (3) orientation assignment, and (4) key point descriptor extraction. In the first stage, the original images are decomposed into a Gaussian pyramid, and each level of the pyramid is called an octave, which is further decomposed into several sub-levels by convolving the initial image at the corresponding pyramid level with DoG filters with different variances. In the second and third stages, many stable key points are detected, and the locations, scales, and orientations of these key points are computed. In the last stage, a SIFT descriptor for each key point is generated.

In this work, we use SIFT to get the key points of handwriting, their SIFT descriptors (SDs), and the corresponding scales and orientations (SOs). The SDs are scale and rotation invariant and can reflect the structures of the image regions centered at the key points and the SOs can preserve the scale and orientation information of these structures. Both SD and SO are very important information of handwriting to distinguish different writers. Therefore, in the following subsections, these SIFT information will be used to extract features of handwriting for writer identification.

D. Codebook Generation

Given a handwriting document image, many word regions (WRs) are obtained after word segmentation. For each WR, we use the SIFT algorithm to detect a number of key points and extract their descriptors, scales, and orientations. Fig. 3 shows an example of the key points detected in a word region by using SIFT. We may obtain a large and varying amount of key points from different handwriting images. It is very difficult, if not impossible, to keep all of the key points' SDs and SOs as features for writer identification. To make the number of the features limited and fixed, we cluster the SDs of the key points extracted from the training samples into N categories and represent each category with its center, which is called a code. All of the N codes form a SD codebook with size N. And based on the codebook, we will compute a histogram with limited and fixed dimension as feature vector for writer identification in the following subsection.

In this work, the hierarchical Kohonen SOM clustering algorithm [32], which has been successfully used for codebook generation in offline text-independent writer identification [3], is chosen to generate the SD codebook, and N is empirically selected as 300.

E. Feature Extraction

Since the text in the identifying handwriting document may be totally different with the text in the enrolled handwriting document in offline text-independent writer identification system, the layout of the key points may be totally different in the different handwriting images, even if they are written by the same person. Therefore, we will not consider the positions of the key points in the following feature extraction and matching. We just take into account the frequency of each SD and SO occurrences in a handwriting image.

1) SIFT Descriptor Signature (SDS) Extraction: Let $SD = \{d_1,\ d_2, \ldots, d_n\}$ denote n SIFT descriptors (SDs), which are extracted from an offline handwriting image I, and let $C = \{c_1,\ c_2, \ldots, c_N\}$ denote a SD codebook with size N. The process of SDS feature extraction is presented as follows.

1. Initialize the SDS feature vector with size N by $SDS = (0,\ 0, \ldots, 0)$.
2. For each $d_i \in SD$, compute the Euclidean distance between it and each code word $c_j \in C$ as below:

$$ED_{ij} = \sqrt{\sum_{k=1}^{L} (d_{ik} - c_{jk})^2}. \tag{1}$$

   where $L = 128$ is the size of the SIFT descriptor. And a Euclidean distance vector EDV for d_i is obtained as below:

$$EDV = (ED_{i1},\ ED_{i2}, \ldots, ED_{iN}). \tag{2}$$

3. Sort the components of EDV in ascending order and obtain the top t components' index in EDV, denoted as

$$IDX = \{idx_1,\ idx_2, \ldots, idx_t\} \tag{3}$$

4. For each $idx \in IDX$, update the SDS feature vector as follows:

$$SDS_{idx} = SDS_{idx} + \delta(EDV_{idx}) \tag{4}$$

   where $\delta(x)$ is a non-increasing function.
5. Repeat step 2 to 4 until all SDs are processed.
6. Compute the final SDS vector as follows:

$$SDS_i = \frac{SDS_i}{\sum_{j=1}^{N} SDS_j}. \tag{5}$$

The parameter t is database-dependent and can be determined by using cross-validation on the training dataset. The function $\delta(x)$ can be selected as some decreasing functions, as done in [33]. However, after testing different functions, such as inversely proportional functions, exponential functions and constant functions, etc. we find that the performances with constant functions are the best. Therefore, this work employs the constant function $\delta(x) = 1$ to construct SDS features.

2) Scale and Orientation Histogram (SOH) Extraction: In this work, the handwriting images are decomposed into X octaves and Y sub-levels in each octave, i.e. $Z(= X \times Y)$ scales, by using SIFT. Let $S = \{s_1, s_2, \ldots, s_n\}$ denote n SIFT key points' scales, $1 \leq s_i \leq Z$, and let $O = \{o_1,\ o_2, \ldots, o_n\}$ denote the corresponding orientations of

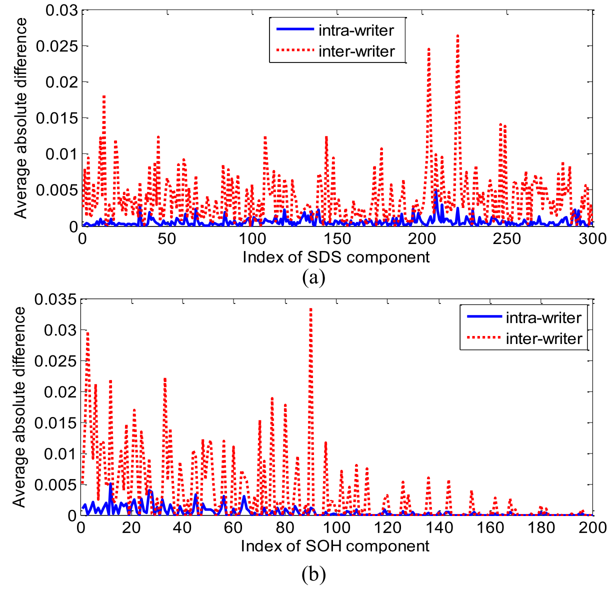


Fig. 4. Examples of difference of SDS and SOH between intra-writer and inter-writer. (a) SDS feature differences. (b) SOH feature differences.

these SIFT key points. Give an angle step ϕ, the orientation $[0,\ 360]$ can be quantized to $Obin = \lceil 360/\phi \rceil$ intervals, where $\lceil x \rceil$ is an operator to get the nearest integer which is greater than or equal to x. The process of SOH feature extraction is presented as follows.

1. Initialize the SOH feature vector with size $M = Z \times Obin$ by $SOH = (0,\ 0,\ \ldots, 0)$;
2. For each key point's scale and orientation, $s_i \in S$ and $o_i \in O$, compute its index idx in SOH feature vector as follows:

$$\begin{aligned} bin &= \lceil o_i/\phi \rceil \\ idx &= Obin \times (s_i - 1) + bin \end{aligned} \tag{6}$$

3. Update the SOH feature vector as follows:

$$SOH_{idx} = SOH_{idx} + 1 \tag{7}$$

4. Repeat step 2 and 3 until all key points are processed.
5. Compute the final SOH feature vector as follows:

$$SOH_i = \frac{SOH_i}{\sum_{j=1}^{M} SOH_j}. \tag{8}$$

In this work, the parameter X and Y are empirically selected as 6 and 3 by extensive experiments, and ϕ is database-dependent and can be determined by using cross-validation on the training dataset.

Fig. 4 shows the average absolute differences of each component of SDS and SOH between ten positive and negative pairs. According to this figure, the difference between inter-writer is much larger than the difference between intra-writer for both SDS and SOH, which means that both SDS and SOH have strong discriminability to different writers. From Fig. 4(b), we find that the differences of the components with large index in SOH become smaller and smaller with the increase of the index. According to the construction of SOH, the large indexes correspond to large scales. With the increase of scales, the handwriting image becomes increasingly blurred and more detailed structures are missed at larger scales. Therefore, the number of the SIFT key points detected at large scales become much less than those at small scales, which results in the decrease of the values (and hence the differences) of components with large indexes (scales) with the increase of index (scale).

TABLE I

OVERVIEW OF THE DATASETS USED IN EXPERIMENTS

Dataset	Writers	Language
IAM	657	English
Firemaker	250	English
ImUnipen	215	English
HIT-MW	241	Chinese
ICDAR2011	8+26	English, French, German, Greek
ICFHR2012	26+100	English, Greek

F. Feature Matching and Fusion

Let I_1 and I_2 denote two handwriting images, and let $u = (u_1, u_2, \ldots, u_N)$ and $v = (v_1, v_2, \ldots, v_N)$ denote their SDSs, and $x = (x_1, x_2, \ldots, x_M)$ and $y = (y_1, y_2, \ldots, y_M)$ denote their SOHs.

In this work, because of its simplicity and high efficiency, the Manhattan distance is adopted to measure the dissimilarity between two SDSs u and v:

$$D_1(u, v) = \sum_{i=1}^{N} |u_i - v_i| \tag{9}$$

As discussed above, the values (and hence the differences) of the components with large indexes in SOHs are much smaller than the ones with small indexes. If we still use the Manhattan distance to measure the dissimilarities between SOHs, the components with large indexes will contribute much less to the dissimilarity than the ones with small indexes. In this paper, the Chi-square distance, which improves the importance of the small value components by giving them more weight, is employed to measure the dissimilarity between SOH x and y:

$$D_2(x, y) = \sum_{j=1}^{M} \frac{(x_j - y_j)^2}{(x_j + y_j)} \tag{10}$$

After normalized both D_1 and D_2 into interval [0, 1], these two distances are then fused to form a new distance to measure the dissimilarity between I_1 and I_2 as below:

$$D(I_1, I_2) = w \times D_1(u, v) + (1 - w) \times D_2(x, y) \tag{11}$$

where $0 \leq w \leq 1$ is a weight. The parameter w is database-dependent and can be determined by using cross-validation on the training dataset.

III. EXPERIMENTAL RESULTS AND ANALYZES

A. Datasets and Criterions

1) Datasets: Our experiments are conducted on six public datasets: three English datasets, i.e. IAM [34], Firemaker [35], and ImUnipen [5], one Chinese dataset HIT-MW [36], and two hybrid-language datasets, i.e. ICDAR 2011 writer identification competition dataset (called ICDAR2011 dataset) [8] and ICFHR 2012 writer identification contest dataset (called ICFHR2012 dataset) [12].

The IAM dataset [34] contains 1539 English handwriting document images from 657 writers. There are 158 writers owning 3 or more handwriting samples. We modify the IAM dataset as described in [5] in our experiments by keeping only the first two documents for those writers who contribute more than two documents and splitting the document roughly in half for those writers with a unique page in the original set. The modified IAM dataset is called MIAM dataset in our experiments.

The Firemaker dataset [35] contains 1000 handwriting pages collected from 250 writers and four pages per writer. Page 1 has a copy text of five short paragraphs with normal handwriting. Page 2 has another copy text of two paragraphs with only uppercase letters. Page 3 contains “forged” text. Page 4 has the content of a given cartoon written by writers in their own words. As done in [5], only Page 1 and Page 4 are used for writer identification in our experiments.

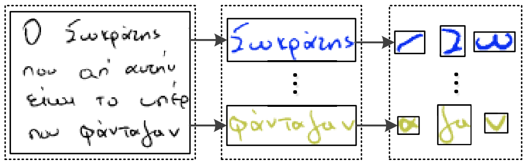
The ImUnipen dataset [5] is the offline version of an online database [37]. It contains handwriting from 215 writers, two samples per writer. As done as [5], we modify the ImUnipen dataset to form MImUnipen dataset by selecting 130 samples from 65 writers in our experiments.

The HIT-MW dataset [36] consists of 853 handwriting Chinese samples, in which 254 images from 241 writers are labeled by ID. Most of the writers have only one page of handwritten text. We modify the HIT-MW dataset to form two new datasets. For the 241 writers’ labeled images, as done in [21], only one page for each writer is used and each page is segmented into two commensurate parts, which form a new dataset, called L-HIT-MW. Through the observation of human eye, 100 handwriting images from 100 different writers are manually selected from the unlabeled images and each image is split into two commensurate parts, which form another new dataset, called U-HIT-MW.

The ICDAR2011 dataset [8] consists of a training dataset and a test dataset, containing 8 writers and 26 writers, respectively. Each writer is asked to copy eight pages that contain text in four languages (English, French, German and Greek) and each language has two pages. A new cropped dataset, called CICDAR2011 dataset, is built by cropping the images of the test dataset, preserving only the first two text lines, in order to decrease the amount of available information.

The ICFHR2012 dataset [12] consists of a training dataset and a test dataset, containing 26 writers and 100 writers, respectively. Each writer is asked to copy four pages of text in two languages (English and Greek). And the number of text lines that are produced by the writers ranges between three and six.

Table I gives an overview of all datasets used in our experiments.



(a) (b) (c)

Fig. 5. Illustration of three different levels of handwriting document image for feature extraction. (a) Page-level. (b) Word-level. (c) Allograph-level.

TABLE II

SOFT TOP-N PERFORMANCE OF THE PROPOSED FEATURES EXTRACTED FROM DIFFERENT LEVEL ENTITIES ON THE MIAM DATASET (%)

Level	SDS		SOH	
	Top-1	Top-10	Top-1	Top-10
Page	74.5	91.4	64	87
Word	**94.2**	**98.9**	**78.4**	**93.7**
Allograph	72	88.8	67.5	88.6

2) Criterions: The most popular criterions including the "leave-one-out" strategy, the soft Top-N, and the hard Top-N criterion for each dataset are employed to evaluate the proposed method on the same dataset. The "leave-one-out" strategy means that for each handwriting document sample, the distances to all other samples of these datasets are computed [5]. The soft TOP-N criterion is defined as that a correct hit is considered when at least one document image of the same writer is included in the N most similar document images [5], [8]. The hard TOP-N criterion is defined as that a correct hit is considered when all N most similar document images are written by the same writer [8]. The hard TOP-N criterions make sense only when at least N reference documents exist for a given writer.

B. Experiments on Different Level Features

For a handwriting document image, the proposed feature extraction method can be used at three levels: page-level, word-level, and allograph-level. Fig. 5 shows some examples of these levels. To select the suitable level features for the following experiments, we respectively adopt MImUnipen and MIAM as training and test datasets to investigate the discriminability of SDS and SOH at these three levels. The "leave-one-out" strategy and the soft TOP-N criterion are used in this experiment. Table II presents the experimental results at different levels. As shown in this table, both SDS and SOH get the best performance at the word-level, which means that these two features at word-level are more powerful to represent the handwriting than at other levels. The possible reasons are listed as below.

1. Word-level features are very stable because when writing a document, each word is always taken as a whole.
2. Page-level features include both the word-level features and the features extracted between the words and between the text lines, which are not stable and hence harmful for writer identification.
3. Allograph-level features are a subset of word-level features, which misses so many features between allographs in the same words. These missing features are also stable and have strong discriminability for different writers.

Therefore, word-level features will be extracted for writer identification in the following experiments. For IAM and HIT-MW datasets, we directly use the word regions provided with the datasets to extract the word-level features. For other datasets, we segment the word regions for word-level feature extraction by using the proposed word segmentation algorithm.

TABLE III

SOFT TOP-N PERFORMANCE OF DIFFERENT APPROACHES FOR WRITER IDENTIFICATION ON THE MIAM DATASET (%)

Approach	Writers	Top-1	Top-5	Top-10
Contour-hinge(GH) [5]	650	81	N/A	92
Grapheme emission(GE) [5]	650	80	N/A	94
GH+GE [5]	650	88	N/A	97
LPQ [19]	650	96.7	N/A	N/A
Siddiqi [23]	650	91	N/A	97
Line fragment [24]	650	93.7	N/A	97.7
GMF [21]	657	90	95	96.3
Contour-hinge(GH) [22]	657	94	N/A	96
Quill–Hinge [22]	657	97	N/A	98
SDS	657	94.2	98.6	98.9
SOH	657	78.4	90.3	93.7
SDS+SOH	657	**98.5**	**99.1**	**99.5**

C. Performances on Different Public Datasets

1) Experiments on English Datasets: In this part, as done in [5] and [24], MImUnipen is used as training dataset, and MIAM and Firemaker are used as test datasets. The "leave-one-out" strategy and the soft TOP-N criterion are used to evaluate the proposed method on these datasets.

Table III lists the writer identification results of different approaches on MIAM. From this table, we find that for the same Contour-hinge feature, the presented results in [22] are much better than the results reported in [5]. That is because different strategies are adopted in these two references. In [22], most writers have 2 to 58 reference samples during identification, while each writer has only one reference sample in [5]. It is not surprised that more reference samples result in better performance. We adopt the same strategy as [5] for the proposed method. Even so, the proposed method with SDS and SOH still outperforms all of the state-of-the-art approaches, including the one presented in [22]. Please note that all images of 657 writers in MIAM dataset are used to test the proposed method while some existing approaches [5], [19], [23], [24] only use 650 writers.

Table IV lists the writer identification results of different approaches on Firemaker dataset. As shown in Table IV, the proposed method also performs better than all of the state-of-the-art approaches. According to Table III and IV, we find that the Top-1 performances of all approaches in MIAM are better than those in Firemaker. The possible reason is that the features extracted from the images in MIAM are much more stable than those extracted from the samples in Firemaker since the average amount of handwritings in images of MIAM is much more than those in Firemaker.

Tables III and IV also show that though the sole SDS or SOH technique may not outperform some state-of-the-art

TABLE IV
SOFT TOP-N PERFORMANCE OF DIFFERENT APPROACHES FOR WRITER IDENTIFICATION ON THE FIREMAKER DATASET (%)

Approach	Top-1	Top-5	Top-10
Contour-hinge(GH) [5]	81	N/A	92
Grapheme emission(GE) [5]	75	N/A	92
GH+GE [5]	83	N/A	94
GMF [21]	78	89.4	92.4
Quill–Hinge [22]	86	N/A	97
Line fragment [24]	91.8	N/A	98.6
SDS	90.6	95.2	97.4
SOH	73.8	89.2	92.8
SDS+SOH	**92.4**	**96.2**	**98.8**

TABLE V
SOFT TOP-N PERFORMANCE OF DIFFERENT APPROACHES FOR WRITER IDENTIFICATION ON THE L-HIT-MW DATASET (%)

Approach	Top-1	Top-5	Top-10
Contour-hinge [21]	84.6	95.4	96.7
Multi-scale contour-hinge [21]	92.5	97.1	97.5
GMF [21]	95	98.3	98.8
SDS	85.8	95.4	98.3
SOH	85	93.8	95.4
SDS+SOH	**95.4**	**98.8**	**99.2**

approaches, the fusion of these two features can get the best performance, which means that SDS and SOH characterize the different aspects of the handwritings and can complement each other.

2) Experiments on Chinese Dataset: For Chinese dataset, U-HIT-MW and L-HIT-MW are respectively used as training and testing dataset. As done in [21], one handwriting image of each writer in L-HIT-MW is used as the query and the other one is used as the reference. Each query handwriting image is compared with all reference images. Table V shows the writer identification performance of different approaches on this dataset. Again, compared with the sole SDS and SOH, the combination of these two features dramatically improves the performance and gets the best results among all of the state-of-the-art approaches, which demonstrates that the proposed method also can work well on the handwritings with complex structures, such as Chinese.

3) Experiments on Hybrid-Language Datasets: ICDAR2011 dataset and ICFHR2012 dataset respectively contain a training dataset and a test dataset. For each dataset, we directly adopt the training dataset to create codebook and determinate parameters, and employ the test dataset for evaluation. The "leave-one-out" strategy, the soft and hard TOP-N criterions are used in this part. As there are eight (four) documents for a given writer with ICDAR2011 (ICFHR2012) dataset, it is possible to compute up to a Top-7 (Top-3) criterion for the hard evaluation: one page as a query, the other seven (three) retrieved as the first references.

Tables VI and IX respectively list the soft and hard Top-N performances on ICDAR2011 and ICFHR2012 datasets. As shown in these tables, the performances of all approaches with the soft Top-N criterion are much better than those with hard Top-N criterion. It is reasonable because the hard Top-N criterion is much stricter than the soft one. With both criterions, the proposed method outperforms all of the state-of-the-art approaches. When the criterion is switched from the soft Top-N to the hard Top-N, the performances of the proposed method drop much less than other approaches, which means that the proposed method is much more stable than other approaches.

Table VI also presents the performances of entire ICDAR2011 and CICDAR2011. Tables VII and VIII respectively list the performances of different language sub-datasets of ICDAR2011 and CICDAR2011. According to these tables, the proposed method get the best results in all of these tests, except the soft Top-5 performance on Greek cropped sub-dataset shown in Table VIII. The performances of all approaches in ICDAR2011 dataset and its sub-datasets are much better than those in CICDAR2011 and its sub-datasets. That is because that the images in CICDAR2011 contain only two lines of handwriting, which is too little to extract stable features for discriminating different writers. As shown in these tables, the performances of the state-of-the-art approaches drop much more than the proposed method, which demonstrates that the proposed method is more robust to the amount of handwriting than other approaches.

To further investigate the robustness to the amount of handwriting, the proposed method is tested again on the ICDAR2011 different languages sub-datasets. One of the images for each writer in the testing dataset is used as the reference sample and the remaining one is employed for query. The reference samples are fixed and a different number of segmented words of the querying image are randomly selected to evaluate the Top-1 performances of the proposed method. This procedure is repeated 100 times and the average Top-1 performances with different number of handwriting words are plotted in Fig. 6. According to this figure, the Top-1 performances on different language datasets increase quickly with the increase of the handwriting word number. For German, English and French, the proposed method can get perfect Top-1 performances when the handwriting word numbers increase to 15, 22 and 63, respectively. And for Greek, the Top-1 performance converges to 96.15% when the word number increases to 25. Fig. 6 also shows that the Top-1 performances of German, English and French have exceeded 97.5% when the images contain only 5, 7 and 9 handwriting words and the Top-1 performance of Greek has exceeded 95% when the image contains only 14 words. That is, the proposed method also works well even when the amount of handwriting is little.

Table X lists the soft Top-N performances of ICFHR2012 English and Greek sub-datasets. As shown in this table, the proposed method also gets the best results among the state-of-the-art approaches.

The above experimental results show that the proposed method works well for five different languages (i.e. English, Chinese, French, German and Greek) and hybrid-languages, which demonstrate that the proposed method is language-insensitive. Also from Tables III–X, we observe that the performance of the proposed method slightly changes in different languages. That's because the characteristic and structures of the words are different for different languages.

TABLE VI

SOFT AND HARD TOP-N PERFORMANCE ON ICDAR2011 ENTIRE DATASET AND ENTIRE CROPPED DATASET (CICDAR2011) (%)

Approach	Soft evaluation						Hard evaluation					
	Entire dataset			Entire cropped dataset			Entire dataset			Entire cropped dataset		
	Top-1	Top-5	Top-10	Top-1	Top-5	Top-10	Top-2	Top-5	Top-7	Top-2	Top-5	Top-7
ECNU	84.6	88	88.9	65.9	81.7	86.5	51	2.9	0	39.4	2.9	0
QUQA-a	90.9	98.1	99	74	91.8	96.2	76.4	42.3	20.2	52.4	15.9	3.4
QUQA-b	98.1	99.5	**100**	67.3	91.8	94.7	92.3	77.4	41.4	47.6	22.6	6.3
TSINGHUA	**99.5**	**100**	**100**	90.9	98.6	99.5	95.2	84.1	41.4	79.8	48.6	12.5
GWU	93.8	98.1	99	74	91.4	95.2	80.3	44.2	20.2	51.4	20.2	6.3
CS-UMD	99.5	99.5	99.5	66.8	83.7	89.9	91.8	77.9	22.1	51.9	22.1	3.4
TEBESSA	98.6	**100**	**100**	87.5	97.6	99.5	97.1	81.3	50	76	34.1	14.4
MCS-NUST	99	99.5	99.5	82.2	96.6	97.6	93.3	78.9	38.9	71.6	35.6	11.1
SDS+SOH	**99.5**	**100**	**100**	**95.2**	**99.5**	**100**	**98.6**	**91.4**	**63.9**	**88.5**	**63**	**31.3**

TABLE VII

SOFT TOP-N PERFORMANCE ON ICDAR2011 DIFFERENT LANGUAGES SUB-DATASET (%)

Approach	Greek			English			French			German		
	Top-1	Top-5	Top-10	Top-1	Top-5	Top-10	Top-1	Top-5	Top-10	Top-1	Top-5	Top-10
ECNU	19.2	19.2	21.2	15.4	15.4	17.3	23.1	23.1	26.9	46.2	46.2	46.2
QUQA-a	76.9	96.2	98.1	78.9	96.2	96.2	94.2	96.2	**100**	86.5	98.1	**100**
QUQA-b	90.4	92.3	94.2	**100**	**100**	**100**	98.1	**100**	**100**	**100**	**100**	**100**
TSINGHUA	92.3	98.1	100	96.2	98.1	**100**	96.2	**100**	**100**	**100**	**100**	**100**
GWU	80.8	90.4	94.2	84.6	96.2	98.1	96.2	**100**	**100**	92.3	98.1	**100**
CS-UMD	**96.2**	96.2	96.2	98.1	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**
TEBESSA	84.6	90.4	94.2	96.2	98.1	**100**	92.3	**100**	**100**	94.2	**100**	**100**
MCS-NUST	94.2	96.2	96.2	96.2	98.1	**100**	**100**	**100**	**100**	**100**	**100**	**100**
SDS+SOH	**96.2**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**	**100**

TABLE VIII

SOFT TOP-N PERFORMANCE ON CICDAR2011 DIFFERENT LANGUAGES SUB-DATASET (%)

Approach	Greek			English			French			German		
	Top-1	Top-5	Top-10	Top-1	Top-5	Top-10	Top-1	Top-5	Top-10	Top-1	Top-5	Top-10
ECNU	11.5	19.2	23.1	13.5	15.4	19.2	46.2	46.2	46.2	21.2	23.1	26.9
QUQA-a	44.2	73.1	90.4	55.8	75.0	82.7	51.9	88.5	92.3	71.2	86.5	94.2
QUQA-b	34.6	76.9	80.8	63.5	90.4	96.2	48.1	84.6	88.5	44.2	84.6	92.3
TSINGHUA	51.9	**98.1**	98.1	76.9	96.2	**100**	80.8	96.2	96.2	84.6	96.2	**100**
GWU	42.3	65.4	76.9	50.0	69.2	82.7	57.7	86.5	92.3	69.2	88.5	92.3
CS-UMD	40.4	67.3	76.9	44.2	69.2	82.7	59.6	84.6	90.4	73.1	90.4	96.2
TEBESSA	42.3	80.8	92.3	69.2	88.5	100	63.5	90.4	94.2	71.2	88.5	98.1
MCS-NUST	55.8	84.6	94.2	67.3	88.5	92.3	65.4	92.3	96.2	78.9	94.2	98.1
SDS+SOH	**80.8**	96.2	**100**	**88.5**	**98.1**	**100**	**98.1**	**100**	**100**	**92.3**	**100**	**100**

TABLE IX

SOFT AND HARD TOP-N PERFORMANCE ON ICFHR2012 ENTIRE DATASET (%)

Approach	Soft evaluation				Hard evaluation	
	Top-1	Top-2	Top-5	Top-10	Top-2	Top-3
TEBESSA-a	92.3	96.5	98.8	99.0	57.5	**38.0**
TEBESSA-b	89.8	94.3	97.8	98.8	57.5	29.3
TEBESSA-c	94.5	97.3	99.3	99.3	65.0	37.8
QATAR-a	70.3	80.8	91.8	95.3	32.3	11.3
QATAR-b	80.0	87.3	95.0	98.0	34.0	15.3
TSINGHUA	92.8	95.8	97.8	98.3	51.5	27.3
HANNOVER	85.5	90.3	95.3	97.3	41.5	22.8
SDS+SOH	**98.0**	**99.0**	**99.5**	**99.8**	**65.3**	**38.0**

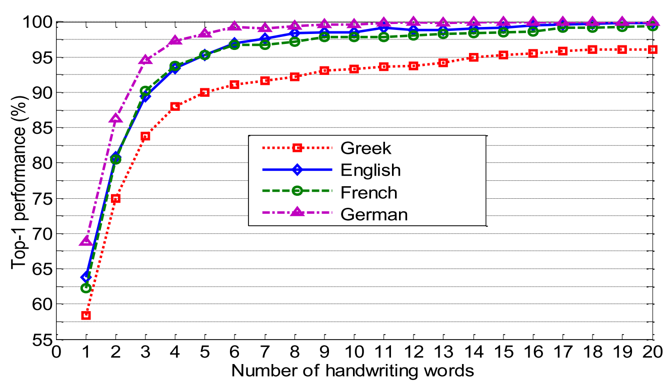


Fig. 6. Top-1 performance of the proposed method with different number of handwriting words on ICDAR2011 different languages sub-dataset.

D. Analysis

In this subsection, we will further analyze the proposed method with Top-1 criterion.

Fig. 7 gives an example which has been identified correctly by the proposed method and false rejected by other approaches, i.e. Contour-hinge [5], Grapheme emission [5], and GMF [21]. From this figure, we observed that the intervals between allographs, and the shapes of special characters such as "t" and "a" are very similar in these two samples, therefore we can judge by the eyes that they are written by the same person. There are two main differences between these two samples shown in Fig. 7. First, the heights of the characters in the top one are much larger than those in the bottom

TABLE X
SOFT TOP-N PERFORMANCE ON ICFHR2012 DIFFERENT LANGUAGES SUB-DATASET (%)

Approach	English				Greek			
	Top-1	Top-2	Top-5	Top-10	Top-1	Top-2	Top-5	Top-10
TEBESSA-a	89.5	**96.0**	97.0	**98.5**	92.0	95.0	98.5	99.0
TEBESSA-b	83.0	90.0	96.0	97.0	85.5	93.5	95.5	99.0
TEBESSA-c	91.5	95.5	97.5	98.0	93.5	97.0	99.5	99.5
QATAR-a	53.5	66.5	85.0	90.0	76.0	96.0	94.5	96.5
QATAR-b	72.5	82.5	92.5	96.5	85.5	90.0	96.0	98.5
TSINGHUA	94.0	94.5	95.5	98.0	90.0	94.0	98.5	99.0
HANNOVER	82.0	88.0	91.5	95.0	87.5	93.0	98.5	99.5
SDS+SOH	**95.5**	**96.0**	**98.0**	**98.5**	**99.0**	**99.5**	**100**	**100**

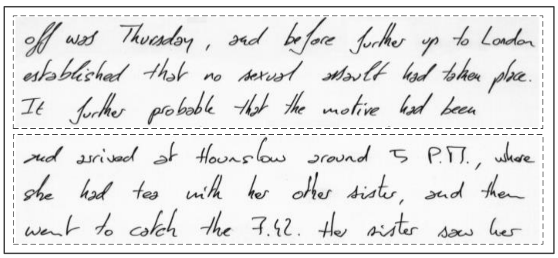


Fig. 7. Two samples from the same writer, which have been identified correctly by the proposed method and incorrectly identified by the state-of-the-art approaches.

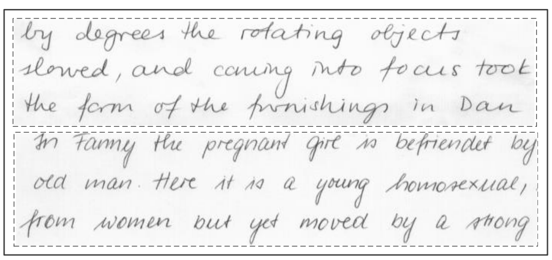


Fig. 8. Two samples from different writers, which have been identified correctly by the proposed method and incorrectly identified by the state-of-the-art approaches.

one while the widths are similar, i.e. the aspect ratios of the characters in these two samples are very different. Second, the top sample is more slant than the bottom one. For the contour or grapheme based approaches, such as Contour-hinge, GMF and Grapheme emission, there is no slant normalization, which makes them sensitive to the slant of the handwritings. The size (or histogram) normalization for Grapheme emission (or Contour-hinge and GMF) can indeed reduce the effect of the size variance of some handwritings. But for the handwritings with the variant aspect ratios, such as the ones in Fig. 7, this normalization cannot make them size invariant. Therefore, these features based approaches incorrectly determined that the handwritings in this figure are from different writers. The proposed method is based on SIFT key points and hence insensitive to the aspect ratio and slant of the characters. Therefore the proposed method can correctly identify these handwriting images.

Fig. 8 demonstrates an example which has been correctly identified from two different writers by the proposed method and incorrectly identified from the same writer by other

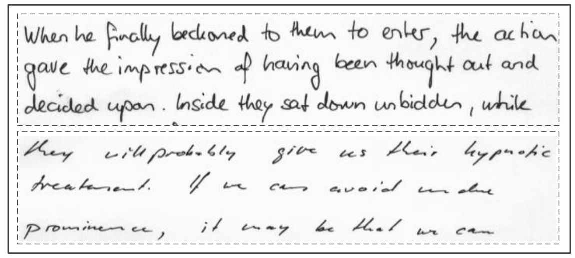


Fig. 9. Example of false rejection. These two samples are from the same writer, but incorrectly identified as different writers.

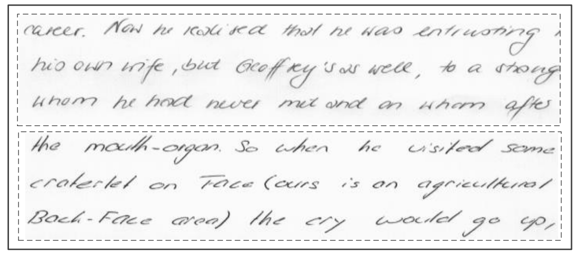


Fig. 10. Example of false acceptance. These two samples are from different writers, but identified as same writer by the proposed method.

approaches, i.e. Contour-hinge [5], Grapheme emission [5], and GMF [21]. As shown in Fig. 8, the two handwritings are very similar in their slant, orientation, and the shape, and hence these state-of-the-art approaches based on the contour or allograph fragments incorrectly identified them from the same writer. However, the allographs of the same word in the bottom sample are more compact than the top one, from which we can know that these two handwritings are written by different writers. The word-level features extracted by the proposed method include the compacting information of a word in a handwriting image. Therefore, the proposed method can correctly identify these handwritings.

Fig. 9 shows an example of false rejection for the proposed method. As shown in this figure, these two handwritings, which were written by the same person, are so different that even the experts may judge by the eyes that they are not from the same writer. The proposed method cannot deal with the handwritings with heavy distortion and fails to identify these handwritings.

Fig. 10 shows an example of false acceptance for the proposed method. As shown in this figure, most of strokes are very similar between these two samples in shape, size, slant, orientation and the compacting information of words. However the experts still can easily decide that the two samples are from different writers by observing the differences between some special strokes (for example, the strokes of letter "g" between the top handwriting and the bottom handwriting in Fig. 10 are totally different). The proposed method computes the frequency of local structure features' occurrences in a handwriting image and the local structures of these few special strokes make very little contribution to feature extraction. Therefore, the proposed method cannot work correctly in this case.

Fig. 11 gives two examples of wrong identification for the proposed method. As shown in this figure, the images contain

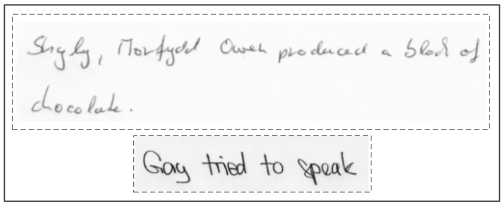


Fig. 11. Examples of wrong identification. These two samples have small amount of handwriting and incorrectly identified by the proposed method.

only several handwritten words. Since the features extracted by the proposed method reflect the frequency of local structure features' occurrences in handwriting images, the amount of handwriting in these two examples is too small to extract stable features to discriminate different writers. Hence, the proposed method fails to identify the right writers.

IV. CONCLUSION

This paper proposes a novel method for automatic offline text-independent writer identification based on SIFT, in which two SIFT features, i.e. SDS and SOH, are extracted from handwriting images to characterize the writer's individuality. The experiments on six public different language datasets demonstrate the power of the proposed method. This method is based on SIFT key points and therefore insensitive to the aspect ratio and slant of the characters. SDS and SOH are very stable and can reflect the structures around the SIFT key points and hence have a strong discriminability to different writers. The word-level features of handwriting are much more suitable to describe the individuality of writers than page-level and allograph-level features since the word is always regarded as a whole when producing the handwriting. The proposed method is language-insensitive and can work well on different languages and hybrid languages, including some languages with complex structures, such as Chinese. The proposed method also works well even when the amount of handwriting is little. In conclusion, the proposed method outperforms the state-of-the-art approaches and is very promising for offline text-independent writer identification with different applications.

REFERENCES

[1] E. Zois and V. Anastassopoulos, "Morphological waveform coding for writer identification," *Pattern Recognit.*, vol. 33, no. 3, pp. 385–398, Mar. 2000.

[2] H. Said, T. Tan, and K. Baker, "Personal identification based on handwriting," *Pattern Recognit.*, vol. 33, no. 1, pp. 149–160, Jan. 2000.

[3] L. Schomaker and M. Bulacu, "Automatic writer identification using connected-component contours and edge-based features of uppercase Western script," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 26, no. 6, pp. 787–798, Jun. 2004.

[4] V. Pervouchine and G. Leedham, "Extraction and analysis of forensic document examiner features used for writer identification," *Pattern Recognit.*, vol. 40, no. 3, pp. 1004–1013, Mar. 2007.

[5] M. Bulacu and L. Schomaker, "Text-independent writer identification and verification using textural and allographic features," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 29, no. 4, pp. 701–717, Apr. 2007.

[6] Z. He, X. You, and Y. Tang, "Writer identification of Chinese handwriting documents using hidden Markov tree model," *Pattern Recognit.*, vol. 41, no. 4, pp. 1295–1307, Apr. 2008.

[7] A. Gordo, A. Fornés, and E. Valveny, "Writer identification in handwritten musical scores with bags of notes," *Pattern Recognit.*, vol. 46, no. 5, pp. 1337–1345, May 2013.

[8] G. Louloudis, N. Stamatopoulos, and B. Gatos, "ICDAR 2011 writer identification contest," in *Proc. Int. Conf. Document Anal. Recognit.*, Beijing, China, 2011, pp. 1475–1479.

[9] A. Hassaine, S. Maadeed, J. Alja'am, A. Jaoua, and A. Bouridane, "The ICDAR2011 Arabic writer identification contest," in *Proc. Int. Conf. Document Anal. Recognit.*, Beijing, China, 2011, pp. 1470–1474.

[10] A. Fornes, A. Dutta, A. Gordo, and J. Llados, "The ICDAR 2011 music scores competition: Staff removal and writer identification," in *Proc. Int. Conf. Document Anal. Recognit.*, Beijing, China, 2011, pp. 1511–1515.

[11] A. Hassaine and S. Maadeed, "ICFHR 2012 competition on writer identification challenge 2: Arabic scripts," in *Proc. Int. Conf. Front. Handwrit. Recognit.*, Bari, Italy, 2012, pp. 835–840.

[12] G. Louloudis, B. Gatos, and N. Stamatopoulos, "ICFHR 2012 competition on writer identification challenge 1: Latin/Greek documents," in *Proc. Int. Conf. Front. Handwrit. Recognit.*, Bari, Italy, 2012, pp. 829–834.

[13] R. Plamondon and G. Lorette, "Automatic signature verification and writer identification—The state of the art," *Pattern Recognit.*, vol. 22, no. 2, pp. 107–131, Feb. 1989.

[14] Y. Zhu, T. Tan, and Y. Wang, "Biometric personal identification based on handwriting," in *Proc. Int. Conf. Pattern Recognit.*, Barcelona, Spain, 2000, pp. 797–800.

[15] R. Hanusiak, L. Oliveira, E. Justino, and R. Sabourin, "Writer verification using texture-based features," *Int. J. Document Anal. Recognit.*, vol. 15, no. 3, pp. 213–226, Sep. 2012.

[16] Z. He, X. You, and Y. Tang, "Writer identification using global wavelet-based features," *Neurocomputing*, vol. 71, nos. 10–12, pp. 1832–1841, Jun. 2008.

[17] L. Du, X. You, H. Xu, Z. Gao, and Y. Tang, "Wavelet domain local binary pattern features for writer identification," in *Proc. 20th Int. Conf. Pattern Recognit.*, Istanbul, Turkey, 2010, pp. 3691–3694.

[18] B. Helli and M. Moghaddam, "A text-independent Persian writer identification based on feature relation graph (FRG)," *Pattern Recognit.*, vol. 43, no. 6, pp. 2199–2209, Jun. 2010.

[19] D. Bertolini, L. Oliveira, E. Justino, and R. Sabourin, "Texture-based descriptors for writer identification and verification," *Expert Syst. Appl.*, vol. 40, no. 6, pp. 2069–2080, May 2013.

[20] L. Maaten and E. Postma, "Improving automatic writer identification," in *Proc. 17th Belgium-Netherlands Conf. Artif. Intell.*, Brussels, Belgium, 2005, pp. 260–266.

[21] X. Li and X. Ding, "Writer identification of Chinese handwriting using grid microstructure feature," in *Proc. 3rd ICB*, Alghero, Italy, 2009, pp. 1230–1239.

[22] A. Brink, J. Smit, M. Bulacu, and L. Schomaker, "Writer identification using directional ink-trace width measurements," *Pattern Recognit.*, vol. 45, no. 1, pp. 162–171, Jan. 2012.

[23] I. Siddiqi and N. Vincent, "Text independent writer recognition using redundant writing patterns with contour-based orientation and curvature features," *Pattern Recognit.*, vol. 43, no. 11, pp. 3853–3865, Nov. 2010.

[24] G. Ghiasi and R. Safabakhsh, "Offline text-independent writer identification using codebook and efficient code extraction methods," *Image Vis. Comput.*, vol. 31, no. 5, pp. 379–391, May 2013.

[25] R. Jain and D. Doermann, "Offline writer identification using k-adjacent segments," in *Proc. Int. Conf. Document Anal. Recognit.*, Beijing, China, 2011, pp. 769–773.

[26] C. Djeddi, I. Siddiqi, L. Souici-Meslati, and A. Ennaji, "Text-independent writer recognition using multi-script handwritten texts," *Pattern Recognit. Lett.*, vol. 34, no. 10, pp. 1196–1202, Jul. 2013.

[27] S. Srihari, S. Cha, H. Arora, and S. Lee, "Individuality of handwriting," *J. Forens. Sci.*, vol. 47, no. 4, pp. 856–872, Jul. 2002.

[28] G. Louloudis, B. Gatos, I. Pratikakis, and C. Halatsis, "Text line and word segmentation of handwritten documents," *Pattern Recognit.*, vol. 42, no. 12, pp. 3169–3183, Dec. 2009.

[29] V. Papavassiliou, T. Stafylakis, V. Katsouros, and G. Carayannis, "Handwritten document image segmentation into text lines and words," *Pattern Recognit.*, vol. 43, no. 1, pp. 369–377, Jan. 2010.

[30] D. Lowe, "Distinctive image features from scale-invariant keypoints," *Int. J. Comput. Vis.*, vol. 60, no. 2, pp. 91–110, Nov. 2004.

[31] D. Nister and H. Stewenius, "Scalable recognition with a vocabulary tree," in *Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit.*, New York, NY, USA, 2006, pp. 2161–2168.

[32] T. Kohonen, "The self-organizing map," *Proc. IEEE*, vol. 78, no. 9, pp. 1464–1480, Sep. 1990.

[33] G. Tan, C. Viard-Gaudin, and A. Kot, "Automatic writer identification framework for online handwritten documents using character prototypes," *Pattern Recognit.*, vol. 42, no. 12, pp. 3313–3323, Dec. 2009.

[34] U. Marti and H. Bunke, "The IAM-database: An English sentence database for offline handwriting recognition," *Int. J. Document Anal. Recognit.*, vol. 5, no. 1, pp. 39–46, Nov. 2002.

[35] M. Bulacu, L. Schomaker, and L. Vuurpijl, "Writer identification using edge-based directional features," in *Proc. 7th Int. Conf. Document Anal. Recognit.* (ICDAR '03), Piscataway, NJ, USA, 2003, pp. 937–941.

[36] T. Su, T. Zhang, and D. Guan, "Corpus-based HIT-MW database for offline recognition of general-purpose Chinese handwritten text," *Int. J. Document Anal. Recognit. (ICDAR '03)*, vol. 10, no. 1, pp. 27–38, Jun. 2007.

[37] I. Guyon, L. Schomaker, R. Plamondon, M. Liberman, and S. Janet, "UNIPEN project of on-line data exchange and recognizer benchmarks," in *Proc. Int. Conf. Pattern Recognit.*, Jerusalem, Israel, 1994, pp. 29–33.

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