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Writer identification using texture features: A comparative study☆

Priyanka Singh*, Partha Pratim Roy, Balasubramanian Raman

Department of Computer Science and Engineering, Indian Institute of Technology, Roorkee, India

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ABSTRACT

A texture-based approach for writer identification of multiple scripts on a single platform is presented in this paper. Potential texture descriptors, namely Local Binary Pattern (LBP), Local Phase Quantization (LPQ), Discrete Wavelet Transform-based Local Extrema Pattern (DWT + LEP), Discrete Wavelet Transform-based Directional and Local Extrema Pattern (DWT + DLEP), Center Symmetric Local Binary Co-occurrence Pattern (CSLBCoP), and Local Tri-Directional Pattern (LTriDP) have been analyzed for identifying the writers. Comparative study for Latin, Arabic, and Devnagri databases was performed, with the Devnagri database contributed by us. The study shows high writer identification rates of 97.62% for IAM dataset using LBP features and Support Vector Machine (SVM) classifier, 95.60% for KHATT database using k-Nearest Neighbor (kNN), and 65.80% for Devnagri scripts using LPQ features and kNN classifier.

1. Introduction

For centuries, numerous graphologists, psychologists, palaeographers, and forensic experts have dedicated their time and energy for carrying out research in the field of handwriting analysis. With exponential advances in tools and technologies, automated systems have been designed for computerized analysis of handwriting [1,2]. Although these tools fetch many advantages such as fast computation of features, efficient usage of search space, visualization, automated segmentation tools, etc., they are still unable to fully replace the human expertise. There exist numerous classical problems that owe their solutions to effective handwriting analysis like the prediction of neurological disorders, spotting of keywords in handwritten fragments, writing styles categorization, prediction of writers' demographics, identification of individuals based on their handwritten documents, etc. [3].

Writer identification generally refers to the task of identifying the author of a given query document based on its match with the known authorship of the handwritten documents present in the database under consideration [4]. It has found numerous utilities in varied applications like signature verification [5], historic document categorization [6], forensic document analysis [7], etc. Based on the kind of written samples considered in the study, these methods can be broadly categorized as offline or online writer identification methods [1,8]. In offline writer identification, the written samples are in the form of digitized images, whereas in online approach, the dynamic information like pen pressure, order of hand strokes, the writing trajectory, etc. are considered using specialized devices [9]. If the same text written by the users is used in the training as well as in the evaluation phases of the system, it is referred to as text-dependent else categorized as text-independent. Text-independent systems are more demanded in real time scenarios [10].

Any writer identification approach initiates with the extraction of features from the samples present in the reference database. These features could be extracted either from the textural or the structural properties of the handwritten documents [11,12]. In

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* Corresponding author.
E-mail address: priyanka.singh@dartmouth.edu (P. Singh).

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texture-based approaches, each writing sample is considered as a different kind of textural pattern and features are extracted based on either the whole document or its different portions. Although many textural features have been proposed in the literature, only few like Local Binary Pattern (LBP) [1,13], Local Phase Quantization (LPQ) [14], etc. have been evaluated in the literature in this aspect. The efficacy of other texture descriptors like Discrete Wavelet Transform-based Local Extrema Pattern (DWT + LEP) [15], Discrete Wavelet Transform-based Directional and Local Extrema Pattern (DWT + DLEP) [16], Center Symmetric Local Binary Co-occurrence Pattern (CSLBCoP) [17], Local Tri-Directional Pattern (LTriDP) [18], etc., needs to be evaluated in this respect. The structural-based approach considers the process of segmenting the handwritten documents based on its structural properties like inter-word as well as intra-word distances, the inclination of the writing, average line height, etc. The proposed prototypical model is an offline text-independent approach for the writer identification problem based on texture features.

1.1. Motivation

The cruciality of the writer identification problem and lack of a uniform platform for comparing the writer identification accuracy for multiple scripts inspired us to propose a prototypical model towards this end. Six textural features were chosen from existing state-of-the-art features depending upon their capability to discriminate the writers via capturing the local patterns based on their neighborhood, multi-resolution property, the co-occurrence of pixel pairs, etc. [15,16]. In our study, we have considered three kinds of scripts, i.e., Latin, Arabic, and Devnagri (one of the popular indian scripts), given their importance [19–21]. As no standard Devnagri dataset was available and realizing its importance, we made an effort towards collecting a substantial amount of data for carrying out this study. The performance of writer identification was tested with different combinations of well-known classifiers and textural descriptors. The results were analyzed along with their dependency on the various parameters considered in the framework and the best performing scenarios were put forward for the multiple scripts on a common platform.

1.2. Our contribution

In this paper, an effort was made for providing a uniform platform for comparing the writer identification accuracy for multiple scripts considering some of the textural features from the existing state-of-the-art features. To attain this objective, we did a thorough study of the existing approaches and found the lacking aspects in this domain. We found that, firstly, no standard Devnagri dataset existed despite the importance and popularity of the Devnagri script. Secondly, although a lot of approaches have been proposed for writer identification of Arabic scripts in the literature, most of them performed it with the Institut fur Nachrichtentechnik (IFN)/ Ecole Nationale d'Ingenieurs de Tunis (ENIT) database which is comparatively a smaller database than the King Fahd University of Petroleum and Minerals Handwritten Arabic TexT (KHATT) which consists of variants of information. The selection of appropriate and fast performing textural features from the existing ones that would better represent the writer information was another challenge. A bunch of six textural descriptors was chosen considering their discriminatory properties. Lastly, we tested the accuracy with different well-known classifiers to investigate the best performing scenarios of writer identification for the multiple scripts considered in the study. In summary, we made the following contributions:

- Collected a substantial amount of Devnagri script samples written by different writers to contribute a Devnagri Dataset to enable the writer identification problem for the same.
- Performed the writer identification task on a large Arabic database, i.e., KHATT that was lacking in the literature for most of the state-of-the-art approaches.
- Selection of six computationally efficient textural descriptors from existing state-of-the-art features and confirming the power of LBP and LPQ in distinguishing the patterns based on co-occurrences of pixel pairs and local patterns existing in the handwritten documents.
- Analyzed the performance of writer identification by considering different well-known classifiers and reported the best performing scenarios for each script.

The rest of the paper has been organized as follows: Section 2 discusses the related work, Section 3 describes the different databases considered in the experimental studies, Section 4 presents the prototypical framework for writer identification. Experimental results with detailed analysis are discussed in Section 5 and conclusion along with the scope of future work is enumerated in Section 6.

2. Related work

Writer identification forms the basis for solving many classical problems of forensics. Hence, it is very challenging and active research area in the field of computer vision and pattern recognition. To identify the writer of a document, we need to identify appropriate features to represent the handwriting, design algorithms to identify handwriting, represent features using the basic methods as well as the derived ones and a comparative evaluation with the existing state-of-the-art approaches.

Based on the level of feature extraction, the writer identification approaches can be categorized as operating at the character level, word level, line level, paragraph level, or document level. For operating at the character level, the features are extracted based on the slant, height, area, pen-input features, structural features, directional features, fuzzy directional features, gradient, structural, concavity features, etc. For the word level operation, morphological features, edge-based directional features, etc., are fetched to fulfill the purpose. To work at line level, connected components enclosing regions, grapheme-based features, fractal and Gabor features, etc., are employed. The next coarser level is the paragraph level where codebook generation, Contourlet Generalized Gaussian Density, Grey-Scale Co-occurrence Matrices, directional features, etc. are employed. For the document level analysis, textural features, allographic features, run length encoding, grayscale histogram, correlation between length, direction, azimuth, pressure, altitude, point distribution method, continuous dynamic programming method, velocity barycenter, etc. are often used.

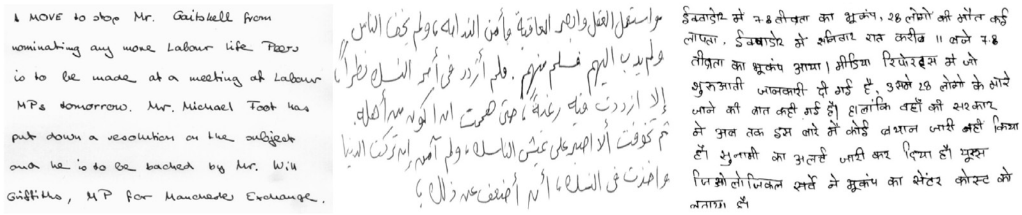
The offine text-independent writer identification approaches can be broadly categorized as either texture-based or structure-based. Although the structure-based approach is more intuitionistic, stable and notable for writer identification, the complexity involved in computing the structural features acts as a limiting factor [10,22,23]. On the other hand, texture-based methods are very simple and treat the handwritten fragments of each writer as a different texture. They extract features from the handwritten fragments working at block level or document level [7,11,12]. Texture-based approaches have the major advantage of fast computational time compared to structure-based approaches as the latter relies on complex feature extraction methods. Although a lot of textural features have been proposed in the literature, their application to writer identification has been studied in few works, such as [11]. They employed LBP proposed by Ojala et al. [13] and LPQ suggested by Ojansivu et al. [14] based features for writer identification on Institutur Informatik und angewandte Mathematik (IAM) and Brazilian Forensic Letters (BFL) Latin-based datasets.

Textural features are very capable in characterizing writers in an effective manner [10,22,24]. Hannad et al. [20] exploited the LBP features for identifying writers in the Arabic handwritten samples. The fast computational efficiency of LBP features along with the local analysis capability contributed towards obtaining very accurate results. However, when the same approach was tested for large databases, its accuracy was found to be significantly decreasing. To improve the accuracy of the writer identification, the scale of observation was brought up to small handwritten fragments and other texture-based features like Local Ternary Patterns (LTP) [25] and LPQ were incorporated besides LBP. It has been proven that writer identification rate varies with the dataset employed for recognition [10]. Same algorithms performing well for Latin datasets may not work well for Arabic datasets. It has been established in the literature that writer identification is tougher for Arabic datasets as compared to Roman scripts. Although many state-of-the-art approaches exist for Arabic dataset, they consider the smaller IFN/ENIT dataset for carrying out their work. Hannad et al. [26] proposed a text-independent writer identification algorithm integrating LBP, LPQ and LTP to improve accuracy for larger Arabic datasets. Though they attained an improvement in writer identification accuracy, a uniform platform was lacking for identifying writer problem for other scripts too. A comparative evaluation for some of the existing state-of-the-art approaches has been listed in Table 1.

In this article, a prototypical framework for writer identification of multiple scripts has been proposed. Different modules of texture block creation, feature extraction, and classifier model were integrated into one framework for writer identification. Towards this cause, six textural features were chosen based on their capability to capture the writer attributes properly from the texture blocks obtained from the handwritten documents. The features employed for this study were as follows: LBP, LPQ, CSLBCoP, DWT + LEP, DWT + DLEP and LTriDP. The framework was tested with classifier models as k-Nearest Neighbor (kNN), Support Vector Machine (SVM), Multilayer Perceptron (MLP), and Random Forest (RF), respectively. The study was carried out for Latin, Arabic as well as Devnagri scripts. As no Devnagri dataset existed in the literature, we contributed a substantial amount of Devnagri dataset to make this study possible. In future, we plan to provide it to the research community for carrying out further research for the Devnagri script.

Table 1
State-of-the-art approaches on writer identification.

Study	Script	Database	No. of writers	Accuracy
[10]	Latin	IAM	650	89%
[20]	Latin	IAM	657	89.54%
[22]	Latin	IAM	650	91%
[2]	Latin	IAM	100	96%
[1]	Latin	IAM	120	96.5%
[11]	Latin	IAM	650	96.7%
[3]	Latin	IAM	50	97.6%
[27]	Latin	IAM	100	97.8%
[12]	Arabic	IFN/ENIT	130	82%
[20]	Arabic	IFN/ENIT	130	87%
[10]	Arabic	IFN/ENIT	350	88%
[9]	Arabic	IFN/ENIT	411	90%
[26]	Arabic	IFN/ENIT	411	94.86%
[28]	Arabic	KHATT	1000	88%
[29]	Arabic	KHATT	1000	92.7%
[23]	Latin	CEDAR	1500	98%
[11]	Latin	BFL	315	99.2%



(a) (b) (c)

Fig. 1. Sample from the datasets (a) IAM (b)KHATT (c)Devnagri.

3. Databases

The proposed system has been tested with three different databases. Two of these are standard Latin and Arabic databases as IAM and KHATT, respectively and the third database is the Devnagri dataset that has been contributed by us. The samples from each of these databases considered in the study are shown in Fig. 1 and detailed description is as follows:

3.1. IAM Database

IAM is one of the most popular English databases that is used for text recognition, writer identification, writer verification and many other applications [21]. It comprises of 1539 forms with handwritten English text of variable content. The images provided in this database are scanned at 300 dpi, 8 bits/pixel, in gray-scale format. The database consists of handwritten documents from 657 different subjects. In total, 13,353 labeled and isolated English text lines written by different subjects are incorporated. There are 350 writers with only one page, at least 300 writers with two pages, and 125 writers with at least four pages of handwritten documents. The database was first published by Marti and Bunke at the ICDAR 1999 [30]. Using this database, a Hidden Markov Model (HMM)-based recognition system for handwritten sentences was developed and published at the ICPR 2000 [31]. The segmentation scheme used in the second version of the database was documented and published in the ICPR 2002 [21]. From the first to the second version of IAM dataset, the size of the database was grown almost twice in size. Also, detailed description of the image processing routines like segmentation of lines of text into individual words, etc. that were part of the database were included in this second version so that recognition experiments could be done more efficiently without the need of developing these routines. For our study, we have used IAM-database version of October 2002.

3.2. KHATT Database

KHATT is the transliteration of the Arabic word which implies ‘handwriting’ [19]. Text recognition related to Arabic characters was impeded due to lack of a freely available comprehensive dataset until KHATT was made available. KHATT is an Arabic database consisting of offline handwritten texts. It is composed of 1000 handwritten forms written by 1000 different writers belonging to different countries. The forms are available at different resolutions of 200, 300, and 600 dpi, respectively. The database contains almost all the Arabic characters collected from 46 different sources and consists of 2000 text paragraphs containing 9327 lines. The database is divided into sets of 70%, 15%, and 15% handwritten documents for exhaustive training, testing, and verification phases. This could facilitate usage of database efficiently and carry out the comparative study properly. Segmented paragraphs from pages and lines from paragraphs are also available to support research at finer levels.

3.3. Devnagri database

The database used in this study is the Devnagri Database which is comprised of 60 writers, two samples per writer, summing to 120 images. Even though Devnagri is one of the popular indian scripts, there was a lack in literature for a comprehensive Devnagri dataset, which motivated us to contribute towards this database. The demand for writer identification is continuously growing from Devnagri forensic experts and Central Bureau of Investigation. The samples of this dataset were acquired mainly from undergraduate students and staff members of Indian Institute of Technology, Roorkee on request, under individual supervision in two different sessions during two months. The age of undergraduate students ranged from 17 to 23. All the writers were native Devnagri speakers and were asked to write two paragraphs each with the freedom of choosing any content they liked. The texts were collected on an A4 white sheet of paper with the liberty of choosing any pen, which implies variety of pens were used. The collected document pages contained handwritten transcripts from Devnagri books, manuscripts, and articles from Devnagri newspapers. The handwritten documents were scanned using a flatbed scanner with 300 dpi pixel resolution in the colored format. The grayscale version of the document images is also made available in the database.

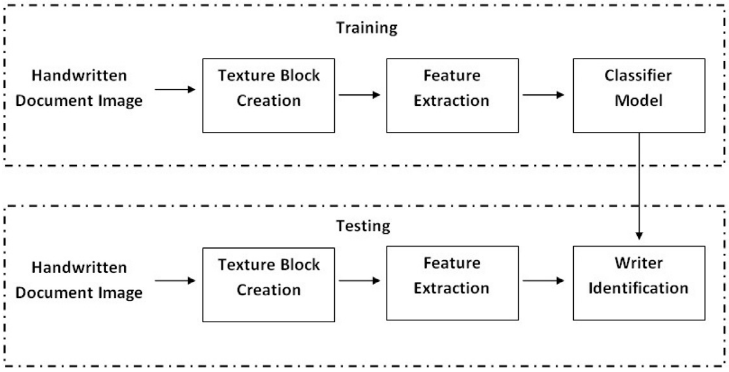


Fig. 2. Prototypical framework for writer identification.

4. Prototypical framework for writer identification

From the study of state-of-the-art approaches, we realized that a uniform platform for writer identification of multilingual scripts was required. In this paper, an effort has been made towards this end by integrating different modules of texture block creation, feature extraction and classifier model for writer identification. The basic flowchart of the proposed model is depicted in Fig. 2 and detailed as follows:

4.1. Texture block extraction

For each handwritten document, a set of nine texture blocks were created using the novel algorithm suggested by Hanusiak et al. [4]. In this method, the text was aligned independently of the way the text was drafted. Rearrangement of all the connected components was done to reduce space between characters, words and lines of text. Each document was binarized using the global thresholding method [32] and scanned throughout to detect all the connected components in the image. The 8-neighborhood connectivity was considered to do so. Small components such as commas, periods, etc. were discarded. The remaining components were aligned using the center of mass of the bounding boxes. The average height h of all the connected components was used to compute the y co-ordinate of the next line as follows:

$$y_{nextline} = y_{previousline} + \frac{h}{2} \tag{1}$$

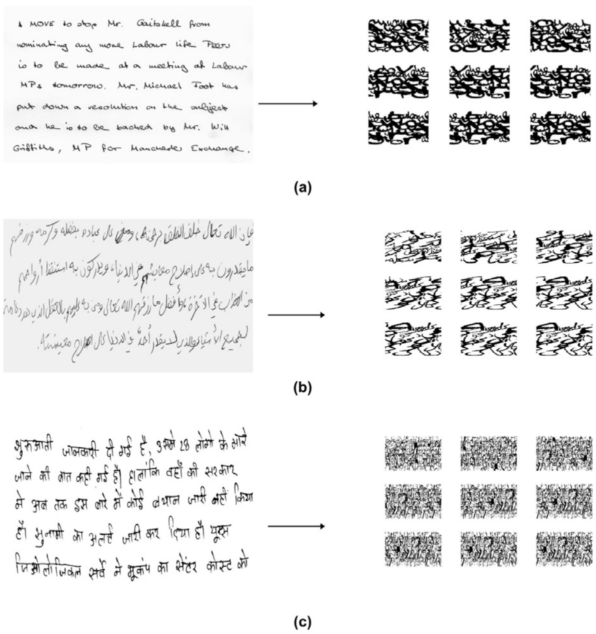


Fig. 3. Input samples with the corresponding texture blocks for (a)IAM (b)KHATT (c)Devnagri databases.

Table 2
Texture descriptors used in the study.

Texture descriptor						
	LBP	LPQ	DWT + LEP	DWT + DLEP	CSLBCoP	LTriDP
Dimension	1 × 256	1 × 256	16 × 7	12 × 512	4 × 256	3 × 256

In case of the first line, $y_{previousline}$ was taken to be 150 arbitrarily. To obtain concise and compact texture blocks, $\frac{h}{2}$ was used to obtain lesser gaps in between the lines. The connected components were further separated to obtain the small fragments which served as the basic matching unit. A pictorial representation of the different texture blocks obtained from processing a sample paragraph for each of the three databases considered in our study is shown in Fig. 3. The fragments were then processed further to obtain a set of six features which characterizes their writer.

4.2. Feature extraction

To characterize the writer of each handwritten document, a set of six features were considered namely LBP, LPQ, DWT + LEP, DWT + DLEP, CSLBCoP, and LTriDP. The dimensions of the texture descriptors employed in the study are enumerated in Table 2 with details of each texture descriptor as follows:

4.2.1. LBP

LBP [13] is one of the fastest and efficient texture descriptors. It is based on the concept of thresholding each pixel with its neighboring pixels in a defined neighborhood and thereafter, computing the weighted power of 2. For a pixel at position (*x, y*), the LBP can be expressed in decimal form as follows:

$$LBP_{P,R}(x, y) = \sum_{i=0}^{P-1} s(g_i - g_c)2^i \tag{2}$$

where P is the number of neighbors, g_c and g_i represent the gray level values of the central and the surrounding pixels in neighborhood of radius R with $s(x)$ defined as follows:

$$s(x) = \begin{cases} 1 & if \;\; x > =0 \\ 0 & otherwise \end{cases} \tag{3}$$

LBP is computed for each of the pixels in the texture blocks and the histogram of these patterns characterizes the writer fragment. Another variant of LBP was introduced in the literature to compact the histogram to a 59 bin histogram called as uniform pattern LBP [33]. Although the speed increased, the performance decreased. In the proposed study, we have considered the original LBP that considers non-uniform patterns for discriminating the small handwritten fragments, thus, resulting in a 256-bin histogram.

4.2.2. LPQ

LPQ [34] is based on the blur invariance property of the Fourier phase spectrum. It extracts the local phase information using the short term Fourier transform which is a 2D Discrete Fourier Transform (DFT). For each position x of a given image $f(x)$, a rectangular neighborhood N_x is considered to compute as follows:

$$F(u, x) = \sum_{y \in N_x} f(x - y)e^{-j2\pi u^T y} = w_u^T f_x \tag{4}$$

where w_u represents the basis vector of 2D-DFT at frequency u and f_x is another vector containing all M^2 image samples from N_x. In LPQ, only four complex coefficients are considered corresponding to 2D frequencies $u_1 = [a, 0]^T$, $u_2 = [0, a]^T$, $u_3 = [a, a]^T$, and $u_4 = [a, -a]^T$, where a is a sufficiently small scalar to satisfy $H(u_i) > 0$, where H is the DFT of Point Spread Function (PSF) of the blur. For each pixel position, this results in a vector:

$$F(x) = [F(u_1, x), F(u_2, x), F(u_3, x), F(u_4, x)] \tag{5}$$

Based on the signs in the real and imaginary part of each component in $F(x)$, the phase information is recorded in the Fourier coefficients as follows:

$$q_j = \begin{cases} 1 & if \;\; g_j \geq 0 \\ 0 & otherwise \end{cases} \tag{6}$$

where g_j is the j^{th} component of the vector.

The histogram of the integer values for all the pixel positions is computed to form a feature vector used for writer characterization.

4.2.3. DWT + LEP

DWT + LEP [15] integrates the benefits of both the multi-resolution property of DWT and the neighborhood relationship of Local Extrema Pattern (LEP) (center pixel to its adjacent pixels in 0 and 180-degree locations). It extracts both directional and textural information from the image as DWT enhances the features of the image by decomposing it into four sub-bands which are obtained by applying low pass and high pass filters. After extraction of texture features, a region-based fragmentation is applied for matching image regions. LEP is a modified form of LBP in which the relationship of neighborhood pixels in same direction is considered to obtain the local pattern. Each of the 8 neighboring pixels corresponding to the center pixel is taken and its adjacent pixels (0 and 180 ° locations) are checked. If both the adjacent pixels are greater or less than that pixel, then a value '1' is assigned to it, otherwise a value '0' is assigned to it. In this way, a binary value '1' or '0' is assigned to each one of the neighboring pixels which are further multiplied with weights in multiples of 2 and then summed to give the final local extrema pattern.

In our study to obtain DWT + LEP features, 2-level DWT of the grayscale image using Daubechies-4 wavelet filters was computed which resulted in seven sub-bands. LEP was calculated for each of these seven sub-bands to yield seven local extrema pattern maps. To obtain the final feature vector, the histograms from all the seven sub-bands were concatenated to get the final feature vector of length 16 × 7.

4.2.4. DWT + DLEP

DWT + DLEP [16] is a modified form of LEP where the relationship of neighborhood pixels in same direction is considered to obtain the value of local pattern. Here, contrary to LEP, only 4 of the neighboring pixels (0, 45, 90, and 180 degree locations) corresponding to the center pixel is taken and their adjacent pixels (0 and 180 ° locations) are checked. If both of them are greater or less than that pixel, then a value '1' is assigned to it, otherwise, value '0' is assigned to it. These assigned values are then further multiplied with weights in multiples of 2 and summed to give the final DLEP.

In our study, 1-level DWT of the grayscale image was computed using Daubechies-4 wavelet filter. It was followed by computation of 4 Directional LEP (0, 45, 90, and 135 ° directions) for the approximation band, 2 Directional LEP (0, 90 ° directions) for the detail band and 3 Directional LEP (0, 45, 135 ° directions) for the horizontal and vertical sub-bands, respectively to finally obtain 12 DLEP map patterns along with their corresponding histograms. DLEP of each direction gave a feature vector of length 512. Hence, the final feature vector of length 12 × 512 was obtained to characterize the writer.

4.2.5. CSLBCoP

CSLBCoP [17] integrates Gray Level Co-occurrence Matrix (GLCM) with Center Symmetric Local Binary Pattern (CSLBP) of an image to obtain the feature pattern. CSLBP is based on the computation of differences of a given pixel from its center symmetric pixels [17]. Based on the differences, binary numbers are assigned to the center symmetric pixels. The greater difference is given value '1', while the smaller one is given value '0'. These binary values are further multiplied by weights corresponding to the pixels in multiples of 2 and summed up to one value, that is called center symmetric local binary pattern value. GLCM is based on computing mutual occurrence of pixel pairs for a specific distance and in a particular direction.

In our study, CSLBCoP was obtained by first computing CSLBP map of the grayscale image followed by GLCM of unit distances at 0,45,90, and 135 degree directions to obtain four matrices corresponding to each direction. Thereafter, all four matrices were converted to vectors and concatenated together to obtain a single feature vector.

4.2.6. LTriDP

LTriDP [18] takes into account the local intensity of pixels based on three directions in the neighborhood. It also considers magnitude pattern for better feature extraction. For each pixel, three difference values D_1, D_2, and D_3 based on the previous, next and center pixels were computed along with two magnitude values. A functional value was created based on the relation:

$$f(D_1, D_2, D_3) = g(D_k) mod(3) \tag{7}$$

where D_1, D_2, D_3 represent the difference values, $g(D_k)$ is the number of times $D_k < 0$ for all $k = 1, 2, 3$

The LTriDP value was then given by:

$$LTriDP(I_c) = \{f_1, f_2, \ldots f_8\} \tag{8}$$

where I_c denotes the center pixel and $1, 2, \ldots, 8$ are the 8-neighborhood pixels.

These values as well as the magnitude pattern were binarized and multiplied with weights in powers of 2 to obtain the histograms that were concatenated to get the final pattern.

5. Experimental results and analysis

To test the suitability of the textural features for writer identification, a series of experiments was performed considering three kinds of scripts, i.e., Latin, Arabic, and Devnagri. The experiments were simulated on a PC with the following configuration: Intel Pentium 2020M with a RAM of 10 GB. The experiments can be categorized into three main sections: Performance of individual textural features for writer identification, comparative study with existing state-of-the-art approaches and the sensitivity analysis to the various parameters considered in the study. The detailed description is as follows:

Table 3
Accuracy assessment (in %) for writer identification based on various classifiers for IAM, Arabic, and Devnagri datasets.

Feature	IAM dataset				Arabic dataset				Devnagri dataset			
	kNN	**SVM**	**RF**	**MLP**	**kNN**	**SVM**	**RF**	**MLP**	**kNN**	**SVM**	**RF**	**MLP**
LBP	95.90	**97.62**	86.90	95.20	**95.60**	85.60	94.80	80.50	64.20	59.90	62.00	59.60
LPQ	95.46	32.40	87.55	51.40	92.30	89.20	89.90	85.80	**65.80**	59.60	61.50	57.50
DWT+ LEP	78.34	76.62	55.20	75.60	79.00	78.30	72.00	75.80	59.20	55.20	54.50	49.30
DWT+DLEP	73.20	75.17	56.80	73.13	89.80	73.00	87.80	76.00	61.10	49.00	52.10	48.00
CSLBCoP	96.70	92.47	86.04	91.60	94.80	75.20	95.20	72.30	63.70	44.20	61.60	42.30
LTriDP	8.98	15.47	15.31	10.34	55.60	54.20	45.60	44.30	32.50	34.80	32.10	24.70

5.1. Performance of individual textural features for writer identification

To evaluate the efficacy of individual textural features in identifying the writer properly, the databases were validated by 10-folded cross-validation technique. We have used linear kernel for SVM. The system has been tested with different values of cost parameter (C). The values were in the range {10, 100} with an interval of 10, {1, 10} with an interval of 1, and {0.1, 1} with an interval of 0.1. The optimum value of cost parameter (C) was found to be 1. The values of other parameters used in the experiments were R for LBP taken as 3, N_x used for LPQ as 8, and 'k' for kNN was set to 3. The accuracy of the system was evaluated with the parameter formulated as follows:

$$Accuracy = \frac{Total\ number\ of\ blocks\ correctly\ retrieved}{Total\ number\ of\ blocks\ present\ in\ the\ database} \tag{9}$$

The performance of the proposed model for each of the three scripts: Latin, Arabic, and Devnagri is detailed as follows:

5.1.1. Evaluation for IAM database

The database comprises of 657 different writers comprising of 1539 different forms. For each form, a set of 9 texture blocks were created and feature vectors were computed on the block basis. An accuracy of 97.62% was obtained using the LBP feature and SVM classifier, whereas using kNN and CSLBCoP feature, an accuracy of 96.70% was reported. The accuracy obtained under different features and classifiers have been tabulated in Table 3 for further reference for writer identification using different textural descriptors for IAM Dataset.

5.1.2. Evaluation for KHATT database

The database comprises of 1000 different writers with each of them contributing 2 pages of handwritten documents. Hence for each author, a set of 18 texture blocks were obtained and the feature vectors were computed for each of these blocks. An accuracy of 95.60% was obtained using kNN classifier and LBP feature. Further results are tabulated in Table 3 for writer identification using different textural descriptors for KHATT Dataset.

5.1.3. Evaluation for devnagri database

The database comprises of 60 writers with each contributing two pages of handwritten documents. Hence for each author, a set of 18 texture blocks were obtained and the feature vectors were computed for each of these blocks. Since the Devnagri script has modifiers in the upper zone as well as the lower zone, the texture descriptors were unable to capture the information properly. Hence, many of the modifiers were categorized as outliers and ignored in the formation of texture blocks. A maximum accuracy of 65.80% was obtained using LPQ feature and kNN classifier. The results are tabulated in Table 3 for writer identification using different textural descriptors for Devnagri dataset. LTriDP is observed to be performing poorly. Although LTriDP considers different directions for the neighborhood pixels, these pixels are taken in vertical or horizontal directions and for handwriting, usually the strokes are aligned in 45–60 degrees which may be the possible cause for LTriDP performing so poorly.

5.2. Performance comparison with state-of-the-art approaches

The aim of this study was to bring out the appropriateness of different textural features for the task of writer identification on a uniform platform and tested with multiple scripts. Hence, it becomes imperative that we compare our obtained results with the existing state-of-the-art approaches. Though Devnagri script is one of the popular Indian scripts, no dataset is available for it and no such work exists in the literature for writer identification of the Devnagri script. In our study, we made an effort to first collect a Devnagri dataset and then carry out the study that was lacking. An accuracy of 65.80% was obtained for 60 writers. The writer identification accuracy obtained for Latin and Arabic scripts have been discussed as follows:

5.2.1. Comparative study for Latin script

For the Latin script, writer identification has been performed for IAM dataset. In our study, we achieved the best results for LBP and CSLBCoP textural features as compared to other features considered in the study. The comparison with other state-of-the-art approaches is tabulated in Table 4.

Table 4
Performance comparison of writer identification for Latin script.

Approach	No. of writers	Accuracy
[1]	120	96.50%
[2]	100	96.00%
[27]	100	97.80%
[10]	650	89.00%
[3]	50	97.60%
[11]	650	96.70%
[20]	657	89.54%
Our results	**657**	**97.62%**

Table 5
Performance measure of writer identification systems on Arabic script.

Study	Database	No.of writers	Accuracy
[9]	IFN/ENIT	411	90.00%
[10]	IFN/ENIT	350	88.00%
[20]	IFN/ENIT	130	87.00%
[26]	IFN/ENIT	411	94.86%
[12]	IFN/ENIT	130	82.00%
[29]	KHATT	1000	92.70%
[28]	KHATT	1000	88.00%
Our results	**KHATT**	**1000**	**95.60%**
Our results	**IFN/ENIT**	**411**	**98.54%**

5.2.2. Comparative study for Arabic script

For the Arabic script, we have tested considering two Arabic datasets: IFN/ENIT and KHATT. Though many works have been carried out for IFN/ENIT database in the literature, no such work exists for KHATT database to the best of our knowledge. KHATT database is a comparatively much larger dataset than IFN/ENIT, hence we have considered both the databases, and results are tabulated in Table 5 for further analysis.

5.3. Sensitivity analysis

The proposed model for writer identification has sensitivity towards the various parameters considered in the study like the size of text block, number of texture blocks per document image and number of authors considered for carrying out the study. The accuracy of the writer identification varies with these parameters and hence, the variation of these parameters is discussed in length in the following sections to bring out the uniformity of the platform.

5.3.1. Sensitivity to text block size

We have carried out experiments considering five different sizes of text blocks for each of the datasets. The size of the text block determines the texture pattern obtained from the document images. It also reflects the spatial coherence of each pixel so as to ultimately decide upon the best textural feature suitable for each block. The best results are tabulated in Tables 6–8 along with the type of feature and classifier used.

Thus from the results, we can observe a uniformity in the accuracy rates that are obtained for each dataset. As the size of block increases, the accuracy increases reaching an optimal value and thereafter, decreases with increase in the size of blocks. The writer identification accuracy came out to be maximum for texture blocks of size 128 × 256.

Table 6
Performance variation with size of text block for IAM dataset. The best results from combination of size, feature, and classifier are reported here.

Size	Feature	Classifier	Accuracy
128 × 128	LBP	kNN	92.00%
128 × 256	**LBP**	**SVM**	**97.62%**
256 × 256	CSLBCoP	kNN	96.54%
256 × 512	LPQ	kNN	84.70%
512 × 512	LBP	SVM	65.00%

Table 7
Performance variation with size of text block for KHATT dataset. The best results from combination of size, feature, and classifier are reported here.

Size	Feature	Classifier	Accuracy
128 × 128	CSLBCoP	RF	89.80%
128 × 256	**LBP**	**kNN**	**95.60%**
256 × 256	CSLBCoP	kNN	91.32%
256 × 512	LPQ	SVM	89.80%
512 × 512	LBP	kNN	54.32%

Table 8
Performance variation with size of text block for Devnagri dataset. The best results from combination of size, feature, and classifier are reported here.

Size	Feature	Classifier	Accuracy
128 × 128	LBP	kNN	59.80%
128 × 256	**LPQ**	**kNN**	**65.80%**
256 × 256	CSLBCoP	kNN	63.50%
256 × 512	LBP	kNN	54.70%
512 × 512	LPQ	SVM	35.00%

Table 9
Performance variation with no. of text blocks per image.

Dataset	6 blocks Accuracy	9 blocks Accuracy	12 blocks Accuracy
IAM	93.80%	**97.62%**	96.00%
KHATT	91.20%	**95.60%**	94.20%
Devnagri	49.40%	**65.80%**	56.70%

5.3.2. Sensitivity to number of texture blocks per image

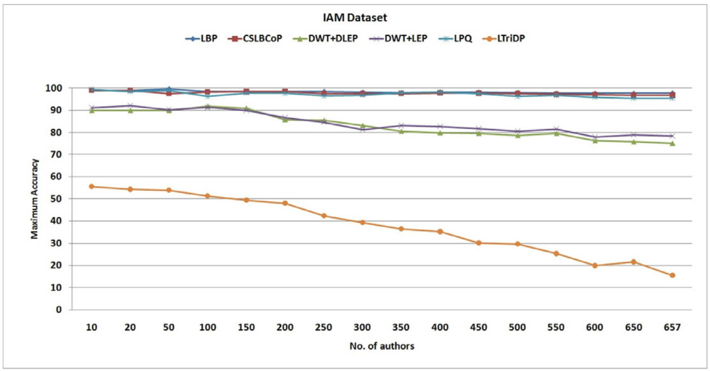
The variation of writer identification with the number of texture blocks per document image has been studied for each of the databases. Number of blocks per document image were fixed to 6, 9, and 12 for uniform training and testing sets of the databases. The optimum results were obtained when it was set to nine blocks per image. For other cases, either the information was not captured properly (in case of six blocks per image) or redundant information was captured (in case of twelve blocks per image). The results are tabulated in Table 9 for further analysis. The best results were achieved with LBP and SVM for IAM dataset, LBP and kNN for KHATT dataset, and LPQ and kNN for Devnagri dataset.

5.3.3. Sensitivity to number of authors

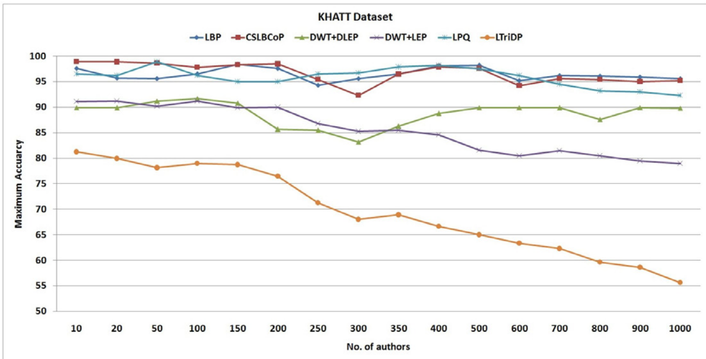
To study the variation of accuracy with respect to the number of writers, we carried out a series of experiments by varying the number of writers. The text block size was set to 128 × 256 and the number of text blocks per image was fixed at nine so as to obtain the optimum performance. For all the three datasets, we observed a gradual decrease in the maximum accuracy as we increased the number of writers. This is absolutely justified with the fact that as the number of writers increases, the content variety increases and hence the system complexity increases giving lesser accuracy. The variation plots are depicted in Fig. 4 for the three databases considered in our study.

6. Conclusion

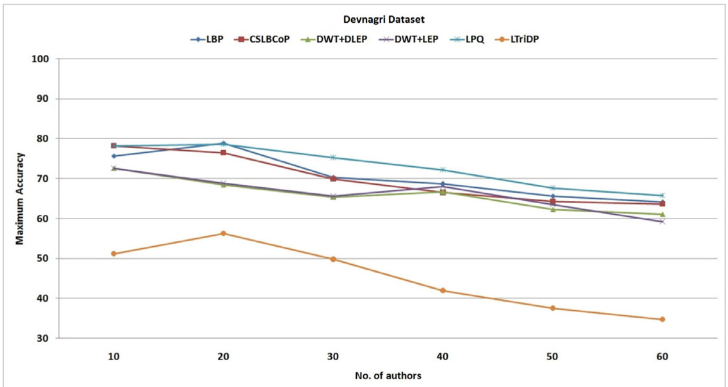
The paper aimed at bringing a substantial amount of transparency in regard to the appropriateness of different textural features for the task of writer identification of multiple scripts. The work was carried out for three scripts: Latin, Arabic as well as Devnagri considering six textural descriptors. Writer identification accuracy was obtained at a sufficiently higher value of 97.62% for IAM dataset with LBP features and SVM as the classifier, 95.60% and 95.20% for Arabic database KHATT using LBP and CSLBCoP as textural descriptors and kNN, RF as classifiers. Further, the work was extended to Devnagri script realizing its popularity and lack of any existing writer identification approach. As no standard dataset existed for Devnagri script, efforts were made towards the contribution of a substantial amount of dataset where work could be performed. We achieved a maximum accuracy of 65.80% using LPQ features and kNN as the classifier for the Devnagri dataset. In future, we aim to provide the Devnagri dataset to the research community so that further research work can be done in this direction. Further improvement in the writer identification accuracy can be analyzed by integrating more structural as well as textural features via different combinations of classifiers.



(a)



(b)



(c)

Fig. 4. Performance variation with number of authors (a)IAM database (b)KHATT database (c)Devnagri database.

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Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.compeleceng.2018.07.003.

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Priyanka Singh is currently working as a postdoctoral fellow in the Department of Computer Science at Dartmouth College, USA. She received her Ph.D. from Motilal Nehru National Institute of Technology in 2016. Her research interests include Encrypted Domain Processing, Image Processing, and Machine Learning.

Partha Pratim Roy received his Ph.D. from Universitat Aut'onoma de Barcelona in 2010. He worked as postdoctoral research fellow in the Computer Science Laboratory (LI, RFAI group), France (2010–2012), and in Synchromedia Lab, Canada (2013). His current research interests include Pattern Recognition and Image Processing.

Balasubramanian Raman received his Ph.D. from Indian Institute of Technology, Madras in 2001. He joined Indian Institute of Technology, Roorkee in 2004, where he works as an associate professor in the Department of Computer Science and Engineering. His research interests include Vision Geometry, Image Fusion, Content-Based Image Retrieval, and Hyperspectral Imaging.