Texture feature column scheme for single- and multi-script writer identification

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Abstract
Identification of writers from images of handwriting is an interesting research problem in the handwriting recognition community. Application of image analysis and machine learning techniques to this problem allows development of computerised solutions which can facilitate forensic experts in reducing the search space against a questioned document. This article investigates the effectiveness of textural measures in characterising the writer of a handwritten document. A novel descriptor by crossing the local binary patterns (LBP) with different configurations that allows capturing the local textural information in handwriting using a column histogram is introduced. The representation is enriched with the oriented Basic Image Features (oBIFs) column histogram. Support vector machine (SVM) is employed as the classifier, and the experimental study is carried out on five different datasets in single as well as multi-script evaluation scenarios. Multi-script evaluations allow evaluating the hypothesis that writers share common characteristics across multiple scripts and the reported results validate the effectiveness of textural measures in capturing this script-independent, writer-specific information.

1 | INTRODUCTION

Study of handwriting and hand-drawn shapes has always remained an attractive subject for historians, document examiners, psychologists and forensic experts. In addition to the semantic content, handwriting is known to carry rich information on the individual producing it \cite{1,2}. The most notable of these is the unique set of writing preferences depicted in the writing style. These writer-specific characteristics allow identifying and authenticating the authorship of a handwriting sample; more commonly known as writer identification and writer verification respectively. Formally, the problem of writer identification involves a set of writing samples with known writers and finding the writer of a handwriting in question, matching it with those in the reference set. The closely related problem of writer verification includes concluding whether a given set of two writing samples come from the same or different writers. Writer identification and verification form an important component of behavioural biometrics \cite{3,4} and although the performance of handwriting as a biometric modality is less impressive as opposed to physiological biometrics (iris, fingerprint, DNA etc.), acquisition of handwriting is non-invasive and does not require any specialised hardware.

With the advancements in image analysis and pattern classification, efforts have been made to develop computerised solutions to analyse digitised images of handwriting. Such systems aim to map the domain knowledge of forensic experts into computational features and these features are employed to
characterise the writer of a handwritten document \[1,5,6\]. From the viewpoint of practical applications, such systems can be employed to facilitate the domain experts by retrieving a hit-list of probable candidates from a large reference set, given a questioned document. This reduces the search space and allows the forensic experts to focus on a limited and manageable set of writing samples for manual analysis and decisive conclusions.

Writer identification can be carried out from online handwriting or offline images in text-dependent or text-independent mode \[7,8\]. From the perspective of offline, text-independent writer identification, computerised solutions exploit the visual differences in handwriting to characterise the writer. These differences include allographic variations, inter-word and intra-word spacings, slope of lines, slant of characters, legibility and cursiveness. Few of such visual differences between the writing samples of two writers can be observed in Figure 1.

This article presents an offline writer identification technique leveraging the rich textural information in handwriting and considering the handwriting of an individual as a unique texture. In other words the technique relies on ‘how’ the text is written rather than ‘what’ is written to characterise the writer. Textural measures based on column histograms of local binary patterns (LBP) and oriented basic image features (oBIFs), computed from images of handwriting, are employed to identify the writer using Support Vector Machine (SVM) as classifier. The proposed technique is evaluated in a single as well as a multi-script mode and high identification rates are realised in a number of experimental scenarios.

The hypothesis that individuals share common characteristics across multiple scripts is inspired by the handwriting generation process. The individuality in handwriting is contributed by many factors which, in addition to the learned copy-book style, include structure of hand, pen grip, muscular strength and properties of the central nervous system \[9\]. Handwriting is produced by a combination of writing strokes—the fundamental units of movement of hand (writing instrument). While the alphabets and words in one script are morphologically very different from those in another script, when produced by the same writer, the same writer-specific combination of writing strokes is employed to generate the final product. Hence, this idea can be employed to carry out writer identification in a script-independent scenario. The existence of common patterns across handwriting samples (of an individual writer) in multiple scripts has also been validated by a number of previous studies \[10-12\] and makes the subject of our current study as well.

The key highlights of this study are listed in the following:

- Investigation of textural measures in characterising an individual from handwriting.
- Crossing multiple configurations of LBP and oBIFs to produce column histograms hence enriching the feature representation.
- Experimental study on five different datasets in a single as well as multi-script scenario.
- Validation of the hypothesis that individuals share common characteristics across multiple scripts.
- Realisation of high identification rates outperforming the current state-of-the-art on this problem.

The article is organised as follows. In the next section, we discuss the recent advancements in offline writer identification. Section 3 introduces the textural features employed to characterise the writer along with the classification details. Experimental study, quantitative performance and a detailed analysis of the reported results is presented in Section 4. Section 5 concludes the article with a discussion on key findings and insights into open research problems on this subject.

2 | RELATED WORKS

Automatic writer identification has matured significantly over the years; thanks to the research endeavours of the pattern classification and handwriting recognition community. While the preliminary attempts targeted isolated characters and text-dependent identification, robust text-independent writer identification techniques have been developed reporting close to 100% identification rates on a hitlist of 10, with reference base of the order of 10\(^7\) matching the target performance for most forensic applications \[9\]. Most of the research on writer identification focused on writing samples in a single-script \[1,13-15\]. A relatively recent trend, however, has been to investigate this problem in a multi-script scenario where same individuals provide writing samples in more than one script \[16,17\]. Investigating common, writer-specific writing characteristics across multiple scripts indeed represents an interesting research problem.

Among various computational features, texture has been a popular choice of researchers for writer characterisation. Bertolini et al. \[13\], for instance, exploit Local phase quantisation (LPQ) and LBP features extracted from normalised blocks of handwriting to identify the writer and report high identification rates on the IAM dataset and the Brazilian Forensic Letter (BFL) dataset. In another similar work, Hannad et al. \[18\] rather than extracting textural measures from blocks, consider small fragments (windows) of writing. In addition to LPB and LPQ, the representation is enriched by a third textural descriptor, the Local Ternary Patterns (LTP). The features are

![Figure 1](image-url) Samples of two different writers—Images in each row represent samples by the same writer.
evaluated in English (IAM) as well as Arabic (IFN/ENIT) writing samples and a comparative performance analysis reveals that LPQ outperforms other descriptors on both the datasets. Among other textural measures, oBIFs [19] computed using a bank of multiple Derivative-of-Gaussian filters, have also shown effective writer identification performance.

Another notable category of writer identification techniques is the codebook-based methods. These methods extract frequent writing patterns to characterise the writer [14]. A codebook of fragmented connected-component contours (FCO3) extracted from character fragments (‘fraglets’), for example is studied in Ref. [20]. The codebook is produced by grouping the fragments using Self Organising Maps (SOMs) and the probability distribution of producing the codebook patterns is used to identify the writer. A similar idea is presented by Siddiqi et al. [21] but rather than considering contour fragments, the codebook is generated using small fragments of writing. In another study [22], a synthetic codebook is employed along with a feature selection scheme to reduce its size. He et al. [23] identify the junction points in handwriting and produce a codebook of ‘junclets’. The idea of codebooks was extended to an ensemble of codebooks (of graphemes) followed by dimensionality reduction in Ref. [24]. In another related work, Khan et al. [25] exploit the bagged discrete cosine transform (BDCT) descriptors to produce multiple codebooks. The final decision on the identity of the writer is reached through majority voting. In a recent investigation [26], key points in the handwriting are identified and patches around the key points are grouped into a codebook to characterise the writer.

In a number of recent studies, automatic feature learning using deep neural networks has also been investigated for writer identification. Authors in Ref. [27], for example exploit convolutional neural networks to learn robust feature representations from writing samples and identify the writer in an end-to-end trainable system. A number of other similar studies [28–31] also demonstrate the effectiveness feature learning for writer characterisation and demonstrate the robustness of learned features over traditional methods. It is, however, important to recall that for a problem like writer identification, while the overall dataset sizes could be of the order of $10^3$, the number of samples per (writer) class is fairly limited. Especially, from the view point of real-world forensic applications, a very limited amount of text (in some cases few lines or words only) is likely to be available. With such limited amount of training data per class, training CNNs to learn features could be challenging. Furthermore, from the perspective of applications for forensic experts, an ‘explainable’ solution is needed for the acceptance of computerised applications in their daily practices. Hand-crafted features are relatively more ‘explainable’ to domain experts as opposed to machine-learned features and the experts can also correlate these hand-engineered features with what they employ in handwriting analysis. In other words, the mapping of domain knowledge to computations features is much more evident. This serves to reduce to hesitancy of these experts in accepting automated solutions to facilitate their analysis.

In the context of multi-script writer identification, Djeddi et al. [32] exploit run-length features with KNN and SVM classifier to identify writers in multi-script experimental settings. Evaluations on a collection of English and Greek writing samples from 126 different writers report promising identification rates. In another work considering the multi-script scenario, Graian et al. [10] employ two-dimensional (2D) auto-regression coefficients to characterise the writer from writing samples in French and Bengali. Likewise, Bertolini et al. [11] study the effectiveness of textural features (LBP and LPQ) in identifying writers in a multi-script experimental protocol with Arabic and English samples of 475 writers from the QUWI database. In another similar work [12], edge-hinge and run-length features are combined to identify writers through samples in Arabic, German, English and French. International competitions on multi-script writer identification have also been organised, the most notable of these include the ICDAR 2015 [16] and the ICFHR 2018 [17] competition.

A summary of well-known contributions to writer identification reported in the literature is presented in Table 1. It is observed that identification of writers from writing samples in a single-script has been thoroughly investigated in the literature and high identification rates have been reported. Writer identification in multi-script settings, on the other, remains relatively less explored. The reported identification rates are also relatively low in many cases. Among popular datasets, IAM and CVL have been widely employed for English while IFN/ENIT and KHATT for Arabic writing samples. It is, however, important to mention that not all of these datasets were collected targeting the writer identification problem. IAM and IFN/ENIT, for instance, were primarily developed for tasks like segmentation and recognition of handwriting. However, since writer information was also stored during data collection, many researchers employed these datasets for evaluation of the writer identification systems. Datasets specifically developed for the writer identification task include the CEDAR letter [1], the BFL dataset [33], ICDAR 2015 writer identification dataset [16] and ICFHR 2018 writer identification dataset [17]. While CEDAR [1] and BFL [33] are collections of single-script samples, many of the recent datasets target writer identification in a multi-script scenario [16,17] and the same is being addressed in our current study.

### 3 | METHODS

Like all pattern classification systems, our writer identification technique relies on two key components, feature extraction and classification. Since we target multi-script writer identification, globally computed features that capture the overall writing style are not likely to be effective as the overall visual appearance of writing samples in different scripts would be totally different (even if they come from the same writer). Local features, on the other hand, allow capturing low-level stroke information in handwriting and this information is independent of script as an individual employs the same set of
writing gestures to produce characters and words irrespective of the script. We, therefore, locally compute textural descriptors to characterise the writer. We introduce a novel representation of the local binary patterns (LBP column histogram) and combine it with the oBIFs column histogram to enrich the representation. Classification is carried out using the SVM classifier. Each of these components is presented in detail in the following.

### 3.1 Column scheme for textural features

Extracting robust feature representations is the core component of any classification system. Given a collection of data samples (handwritten documents in our case) and the corresponding class labels (writer IDs), the idea is to seek effective representation in a feature space where samples of the same class (writer) tend to cluster together while those from other
classes are far apart. In our study, we investigate two textural features, LBP and oBIFs. LBP captures the local spatial patterns in the handwriting. Likewise, oBIFs capture the local symmetry information. Furthermore, in order to capture the same information and different scales of observations, we compute these features for different parameter settings and then compute the column histogram, hence further enriching the representation.

3.2 | LBP column histogram

In continuation of the efforts [34] to seek robust textural representations, LBP descriptor was first proposed in Refs. [35, 36]. It encodes each pixel in an image with a decimal number as a function of the neighbouring pixel values. The encoding works by subtracting the reference pixel from each of its (8) neighbours. If the result is a negative value, the respective neighbour is assigned 1 and 0 otherwise. The resulting binary sequence is then considered as a number and represents the LBP code of the central pixel.

The originally proposed LBP descriptor is considered a local neighbourhood of $3 \times 3$ and could not capture the structural information at distant scales of observations. The descriptor was therefore extended to multiple resolutions [37] by using neighbourhoods of different sizes. The neighbourhood is generalised by considering a circle centred at the pixel to be labelled and is defined by two parameters, the radius $R$ of the circle and the number of (equally spaced) sampling points $P$ in the neighbourhood (Figure 2). Points which do not represent true pixels are interpolated and the neighbourhood is typically represented by the pair $(P, R)$.

The coordinates of $P$ neighbours $(x_p, y_p)$ on the boundary of the circle with radius $R$ are computed with respect to the central pixel $(x_c, y_c)$ as follows.

$$x_p = x_c + R \cos \left( \frac{2\pi p}{P} \right)$$

$$y_p = y_c + R \sin \left( \frac{2\pi p}{P} \right)$$

If the intensity value of the centre pixel is $g_c$ and the intensity values of its neighbours are $g_p$ with $p = 0, 1, 2, \ldots, P - 1$, then the texture $T$ considers the signs of the differences in the local neighbourhood of pixel $(x_c, y_c)$ and is defined as:

$$T \approx (s(g_{0} - g_{c}), s(g_{1} - g_{c}), \ldots, s(g_{p-1} - g_{c}))$$

where, $s(g_p - g_c) = 1$ if $(g_p - g_c) \geq 0$ and 0 otherwise. The local textural information is hence represented as a joint distribution of the value of the centre pixel and the differences. The extended LBP operator [37] is computed by assigning a binomial weight $2^p$ to each $s(g_p - g_c)$ as follows.

$$LBP_{P,R}(x_c, y_c) = \sum_{p=0}^{P-1} s(g_p - g_c) \cdot 2^p$$

where, $P$ is the number of neighbouring pixels and $R$ is the radius of the circle around $(x_c, y_c)$. The histogram of these binary numbers is then used to describe the texture of the image.

LBP is further characterised into uniform and non-uniform patterns. A pattern is termed as uniform if it has at most two bitwise transitions from 0 to 1 (or vice versa) when the pattern is considered a circular string. This results in $P \times (P - 1) + 3$ unique values for $P$ bits. For instance, uniform mapping of 8 sampling points produce 59 unique values while with 16 sampling points, 243 different values are produced.

From the view point of representing a handwriting sample using LBP descriptors, LBP images for different combinations of sampling points $P$ and radius $R$ are computed. These LBP images are then stacked representing each pixel as a column vector. The image is then encoded using a (normalised) histogram of these columns. Figure 3 illustrates the process of computing the LBP column histogram from LBP images corresponding to two sets of $(P, R)$ values. The column histogram enriches the LBP descriptor by taking into account multiple resolutions (scales of observations) corresponding to different values of $P$ and $R$. While the original LBP method considers the local neighbourhood a pixel for a given pair of $(P, R)$ values, we propose to enhance the basic LBP feature by computing two different LBP images for two pairs of $(P, R)$ values, stacking them together and then computing the LBP column histogram that captures much richer local textural and symmetry information in the handwriting image. Different combinations of $(P, R)$ values in computing the column histograms represent different scales at which the handwriting is analysed; combined in a single and enhanced feature vector.

3.2.1 | oBIF column histogram

Another set of textural measures investigated in our study comprises the oBIF. These features have been successfully applied to problems like texture classification [38], digit recognition [39] and identification of writers [19]. In our previous studies, we employed oBIFs for classification of gender from handwriting [40] and identification of writers from...
Three of these symmetry types are accompanied by \( n \) possible orientations, the slope class has \( 2n \) possible orientations while three of the classes do not have any orientation. This gives an oBIF vector of \( 5n + 3 \). More details on computational aspects of oBIFs can be found in our previous work [40].

In the present work, we quantise the orientation into \( n = 4 \) directions, hence producing 23 entries \( (5 \times 4 + 3) \) in the oBIFs dictionary. Similar to the LBP descriptor, oBIFs at two different scales are stacked (by ignoring the symmetry type flat) and the column histogram is computed. The histogram has a total of \((5n + 2)^2 = 484 \) bins. The scale parameter is chosen from the set \( \sigma \in \{1, 2, 4, 8, 16\} \), while \( \epsilon \) is picked from a set of three small values \( \{0.1, 0.01, 0.02\} \). The histogram is finally normalised for subsequent processing.

The LBP and oBIFs column histograms are computed for writing samples of all individuals. By varying the parameters in computation of features, different configurations of LBP and oBIFs are produced and more details on these configurations are presented in Section 4.

### 3.3 Classification

For the identification task, we employ SVM as the classifier [44,45]. The LBP and oBIFs column histograms extracted from the writing sample(s) of an individual are used to train the learning algorithm. SVM is trained with the radial basis kernel function (RBF), the kernel parameter is selected in the range 0, 100, while the soft margin parameter \( C \) is fixed to 10.

For each feature \( x \) fed to the trained SVM classifier, \( n \) decision scores \( f_n(x) \) for \( j = 1, 2, \ldots, n \) are produced. \( n \) is the total number of writers and the decision on the identity of the writer is taken as follows.

\[
f_{\text{max}}(x) = \max(f_n(x); j = 1, 2, \ldots, n)
\]

Equation (5)

\( f_{\text{max}}(x) \) is the maximum value selected from \( n \) responses produced by the classifier and \( f_n(x) \) is the mapping of original SVM output values to the interval \([0, 1]\) as follows.

\[
f_n(x) = \frac{1}{1 + e^{-fx(x)}}
\]

Equation (6)

In addition to making the identification decisions on each of the LBP and oBIFs column histograms, we also report identification performance based on picking the maximum value from the normalised decision scores on each of the two features. There are different ways to combine decisions of classifiers in an attempt to enhance the overall classification rates. Commonly employed methods include majority voting, Borda count, the sum, product and max rules and so on. Since we combine the decisions based on two distinct types of features, combinations using majority voting or Borda count would not be very meaningful (as there are only two scores). For each type of feature (LBP and oBIF columns), the SVM classifier outputs \( n \) similarity scores corresponding to \( n \) writers.

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**FIGURE 3** Different steps of the LBP column scheme: (a) Original image; (b) Both LBPs images at different parameters (LBP image \( p = 4, \ R = 16 \), LBP image \( p = 8, R = 2 \)) are crossed to form columns at each location; (c) Histogram is computed with columns.

historical manuscripts [41]. In the present study, the objective of employing these features is to complement the LBP column histograms and enrich the textural representation of handwriting.

The oBIFs represent an extension to the Basic Image Features (BIFs) [42,43]. The key idea is to label each location in the image with one of the seven local symmetry classes. The features are computed by applying a bank of derivative of Gaussian filters controlled by a scale parameter \( \sigma \). An additional parameter \( \epsilon \) is employed to classify a location as ‘flat’.
in the reference base. As mentioned earlier, these scores are mapped to the interval $[0, 1]$; higher the score, more confident the classifier is in predicting the respective class label (writer). The max rule predicts the output class by choosing the class corresponding to the maximum confidence value among all the participating classifiers. In other words, for the problem under study, the system reports two scores $S_{\text{LB}}$ and $S_{\text{RBI}}$. Selecting the maximum $\max(S_{\text{LB}}, S_{\text{RBI}})$ score ensures that we pick the decision corresponding to the classifier which is more confident. This serves to compensate the errors and improves the overall classification performance. The usefulness of combining decisions of a pair of features using max operator has also been validated in a similar study on gender classification from handwriting [46].

4 | EXPERIMENTS AND RESULTS

The effectiveness of the employed textual measures in characterising the writer is validated through two main series of experiments. The first series of experiments is carried out in the traditional single-script framework where training and test samples of writers are in the same script. These experiments are carried out on two standard datasets, the BFL dataset [33] and the KHATT dataset [47,48]. The second series of experiments is carried out in the more challenging multi-script framework. These experiments involve three different datasets, LAMIS-MSHD [49], WDAD [23] and CERUG [50]. Details of these dataset and experimental protocol are summarised in the following section.

4.1 | Datasets and experimental protocol

As mentioned earlier, the single-script experiments are carried out on the BFL and the KHATT dataset with writing samples in Latin and Arabic respectively. The BFL dataset contains 945 samples from 315 writers (3 samples per writer). The Portuguese text on these samples contain carefully chosen words, character combinations and punctuation marks which are of interest to the forensic examiners, hence making this dataset an attractive choice for evaluation of writer identification systems. In our experiments involving BFL dataset, we carry out three-fold cross validation; in each fold, 630 samples of the 315 writers are used as training set, while the remaining 315 samples of these writers constitute the test set.

KHATT is the second dataset used in our single-script experiments. It comprises of 4000 handwritten samples in Arabic from 1000 different writers. Experiments on KHATT dataset are repeated five times and in each experiment 2000 sampling points are used in the training and 2000 in the test set. Writing samples from BFL and KHATT dataset are illustrated in Figure 4.

For multi-script evaluations, we follow the experimental protocol of the ICFHR 2018 Writer Identification competition [17]. A key aspect of the competition was to evaluate the effectiveness of a writer identification system in learning writer-specific attributes from writing samples independent of the script under study. The competition included six tasks using three datasets LAMIS-MSHD, CERUG and WDAD with writing samples in Chinese, English, Arabic, French and Farsi. Sample images from these datasets are presented in Figure 5 while each of the six tasks is elaborated in the following.

- **Task 1** involves Chinese and English samples from the CERUG dataset. The training set comprises 80 writing samples written in Chinese by 40 different writers while the test set includes 80 unlabelled handwritten images written in English by these 40 writers.
- **Task 2** also involves the CERUG dataset, and the training and test sets of Task 1 are reversed, that is English samples in the training and Chinese in the test set.
- **Task 3** targets Arabic and French samples of the LAMIS-MSHD dataset. About 240 Arabic writing samples of 40 different writers constitute the training set while the test set includes 240 French samples.
• **Task 4** reverses the training and test sets of Task 3.
• **Task 5** is based on samples in the WDAD dataset with 80 different writers. The training set has 160 samples in Farsi while the test set has 160 samples in English.
• **Task 6**, like other tasks, involves swapping the training and test sets of Task 5, that is English samples in the training and Farsi in the test set.

A summary of the distribution of samples and writers in single- and multi-script experimental protocols is presented in Table 2 while the identification rates reported in these experiments are detailed in the next section.

5 | RESULTS AND DISCUSSION

We first report the writer identification rates in the single-script series of evaluations. As mentioned earlier, experiments are carried out to study the impact of different combinations of \((P, R)\) values in the LBP features and the parameter \(\sigma\) in computation of oBIF histogram. The
**TABLE 3** Writer identification rates on the BFL and KHATT datasets

| Dataset | Features | Parameters | Dim. | Average Identification rates (%) |
|---------|----------|------------|------|-----------------------------------|
|         |          |            |      | Top 1 | Top 2 | Top 5 | Top 10 |
| BFL     | $f_1$    | LBP column histogram | LBP at $(P, R) = (16, 2)$ | 14,337 | 98.41 | 99.37 | 99.37 | 100 |
|         |          |            |      | LBP at $(P, R) = (8, 2)$ |      |      |      |      |
|         | $f_2$    | oBIF column histogram | oBIF at $\sigma = 2$ | 529 | 94.92 | 98.01 | 98.01 | 98.01 |
|         |          |            |      | oBIF at $\sigma = 4$ |      |      |      |      |
| KHATT   | $f_1$    | LBP column histogram | LBP at $(P, R) = (16, 2)$ | 14,337 | 75.55 | 86.2  | 92.70 | 94.90 |
|         |          |            |      | LBP at $(P, R) = (8, 2)$ |      |      |      |      |
|         | $f_2$    | oBIF column histogram | oBIF at $\sigma = 1$ | 529 | 63.40 | 64.30 | 76.70 | 83.00 |
|         |          |            |      | oBIF at $\sigma = 2$ |      |      |      |      |
|         |          | Combined decision $(f_1, f_2)$ | – | – | 98.63 | 99.65 |
|         |          |            |      |      | 99.05 | 99.65 |

**TABLE 4** Performance comparison with state-of-the-art features in single-script experiments on the BFL and KHATT datasets

| Feature | Description | Database | Dim. | Classification rates (%) |
|---------|-------------|----------|------|--------------------------|
|         |             |          |      | Top 1 | Top 10 |
| $f_1$   | LBP column histogram | BFL | 14,337 | 98.41 | 100 |
|         |             | KHATT   | 75.55 | 94.90 |
| $f_2$   | oBIF column histogram | BFL | 529 | 94.92 | 98.01 |
|         |             | KHATT   | 63.40 | 83.00 |
| $f_3$   | Combined decision $(f_1, f_2)$ | BFL | – | 98.63 | 99.65 |
|         |             | KHATT   | 77.10 | 94.70 |
| $f_4$   | Run-length distribution on white pixels [32] | BFL | 200 | 95.55 | 97.78 |
|         |             | KHATT   | 56.30 | 85.50 |
| $f_5$   | Run-length distribution on black pixels [32] | BFL | 400 | 84.76 | 96.19 |
|         |             | KHATT   | 22.90 | 50.70 |
| $f_6$   | Run-length distribution on white and black pixels [32] | BFL | 600 | 93.01 | 98.73 |
|         |             | KHATT   | 60.00 | 86.80 |
| $f_7$   | Edge-direction distribution using 16 angles [51] | BFL | 16 | 86.98 | 94.92 |
|         |             | KHATT   | 46.00 | 78.80 |
| $f_8$   | Edge-hinge with fragment of length equal to 7 pixels [51] | BFL | 2304 | 98.20 | 99.04 |
|         |             | KHATT   | 95.50 | 99.10 |
| $f_9$   | Chain code-based global features [21] | BFL | 314 | 95.30 | 98.73 |
|         |             | KHATT   | 65.30 | 89.70 |
| $f_{10}$| Chain code-based local features [21] | BFL | 230 | 83.17 | 89.84 |
|         |             | KHATT   | 47.90 | 78.60 |
| $f_{11}$| Delta hinge feature [52] | BFL | 780 | 32.06 | 55.24 |
|         |             | KHATT   | 64.90 | 81.70 |
| $f_{12}$| COLD feature [53] | BFL | 84*3 | 67.30 | 81.27 |
|         |             | KHATT   | 86.10 | 94.70 |
| $f_{13}$| Implicit shape codebook [26] | BFL | 1428 | 98.33 | 99.67 |
|         |             | KHATT   | 619 | 62.81 | 85.12 |
| $f_{14}$| AR coefficients-based features [10] | BFL | 24 | 92.06 | 97.78 |
|         |             | KHATT   | 40.20 | 77.20 |
evolution of identification rates on BFL and KHATT datasets as a function of different configurations is presented in Figures 6 and 7. It can be seen that the LBP column histogram outperforms the oBIFs column histogram on both the datasets.

A summary of the best performing configurations of LBP and oBIFs column histograms and their combined decision is presented in Table 3. Combining the decisions of the two features (using the max operator) reports (average) Top-1 identification rates of as high as 98.63% and 77.10% on BFL and KHATT datasets respectively. The difference in identification rates on the two datasets can be attributed to the fact that BFL is a text-dependent dataset where all samples of a writer contain the same text. KHATT dataset, on the other hand, contains 2 samples per writer with similar and 2 with unique text making it more challenging. The number of writers in the KHATT dataset is also 1000 as opposed to 315 writers in the BFL dataset.

Prior to reporting the results of multi-script experiments, we first present a performance comparison of the modified LBP and oBIF descriptors in single-script evaluations (Table 4). For a fair comparison, we employed the same experimental protocol and implemented a number of well-known features applied to the writer identification problem. These include run length features ($f_4$-$f_6$) [32], edge direction ($f_7$) and edge hinge ($f_8$) features [51], chain code-based global ($f_9$) and local ($f_{10}$) features [21], delta hinge features ($f_{11}$) [52], COLD features ($f_{12}$) [53], implicit shape codebook features ($f_{13}$) [26] and features based on AR coefficients ($f_{14}$) [10]. An analysis of identification rates presented in Table 4 reveals that the proposed LBP column histogram as well as the combination of LBP and oBIFs report the highest Top1 and Top10 identification rates on the BFL dataset when compared with the well-known state-of-the-art features. For the KHATT dataset, the highest identification rates are reported by edge-hinge features [51] while the proposed feature set reports the third best performance.

Multi-script evaluations represent a more challenging experimental setting as training and test samples belong to different scripts. These experiments are carried out to validate the hypothesis that writers share characteristics which can be common across multiple scripts and, the employed column scheme of textural features is able to capture these writer-specific characteristics. The experimental protocol is same as that of the ICFHR 2018 writer identification competition and summarised in Table 2.

The identification rates corresponding to different configurations of LBP column histograms for the six tasks are summarised in Figure 8 where it can be seen that the identification rates are relatively consistent for different combinations. A similar trend is observed in the case of oBIFs column histograms (Figure 9) where though identification rates of different tasks vary, for a given task, the performance is relatively stable for different combinations of scale values. For both the features, the classification rates of Task 1, Task 2 and Task 4 are relatively higher as compared with those realised in Task 3, Task 5 and Task 6.
For each of the tasks, the identification rates for the best configuration of parameters are summarised in Table 5. Similar to single-script experiments, combining decisions of the LBP and oBIFs column histograms results in enhancing the identification rates as opposed to individual features. The highest reported classification rates (by combining the decisions) read 63.75%, 68.75%, 50.42%, 63.75%, 41.25% and 31.88% on the six tasks.

From the viewpoint of performance comparison with other studies, we first compare the performance of our system with those of the systems submitted in the competition and reported in Ref. [17]. It can be seen from Table 6 that our system reports the highest identification rates in all tasks of the competition using the same experimental settings as that of the participating systems. It is interesting to mention that the systems ‘Tokyo’ and ‘Numberberg’ employed Convolutional Neural Networks for feature extraction. The ‘Tokyo’ method was based on the work reported in Ref. [27] and employed a KNN classifier with CNN features to find the writer of a query sample. Likewise, the ‘Numberberg’ system is based on exploiting CNN activations to characterise writer and is primarily based on the technique reported in Ref. [54].

| Tasks | Column histogram features | Parameters | Dim. | Classification rates (%) |
|-------|---------------------------|------------|------|--------------------------|
|       |                           |            |      | Top 1 | Top 2 | Top 5 | Top 10 |
| Task 1 | $f_1$                     | LBP        |      |       |       |       |       |
|        |                           | LBP at $(P, R) = (16, 4)$ | 14,337 | 62.50 | 71.25 | 83.75 | 92.50 |
|        |                           | LBP at $(P, R) = (8, 8)$ |       |       |       |       |       |
|        |                           | oBIF       |      |       |       |       |       |
|        |                           | oBIF at $\sigma = 1$ | 529  | 57.50 | 67.50 | 80.00 | 86.25 |
|        |                           | oBIF at $\sigma = 2$ |       |       |       |       |       |
|        | Combined decision ($f_1, f_2$) |          |      | 63.75 | 75.00 | 86.25 | 95.00 |
| Task 2 | $f_1$                     | LBP        |      |       |       |       |       |
|        |                           | LBP at $(P, R) = (16, 4)$ | 14,337 | 61.25 | 70.00 | 81.25 | 88.75 |
|        |                           | LBP at $(P, R) = (8, 2)$ |       |       |       |       |       |
|        |                           | oBIF       |      |       |       |       |       |
|        |                           | oBIF at $\sigma = 1$ | 529  | 46.25 | 55.00 | 71.25 | 80.00 |
|        |                           | oBIF at $\sigma = 2$ |       |       |       |       |       |
|        | Combined decision ($f_1, f_2$) |          |      | 68.75 | 78.75 | 87.5  | 91.25 |
| Task 3 | $f_1$                     | LBP        |      |       |       |       |       |
|        |                           | LBP at $(P, R) = (8, 8)$ | 3481  | 37.50 | 51.25 | 72.50 | 81.67 |
|        |                           | LBP at $(P, R) = (8, 4)$ |       |       |       |       |       |
|        |                           | oBIF       |      |       |       |       |       |
|        |                           | oBIF at $\sigma = 1$ | 529  | 37.50 | 50.00 | 68.75 | 80.83 |
|        |                           | oBIF at $\sigma = 2$ |       |       |       |       |       |
|        | Combined decision ($f_1, f_2$) |          |      | 50.42 | 65.83 | 79.17 | 86.25 |
| Task 4 | $f_1$                     | LBP        |      |       |       |       |       |
|        |                           | LBP at $(P, R) = (16, 4)$ | 59,049 | 63.33 | 77.92 | 85.83 | 94.16 |
|        |                           | LBP at $(P, R) = (16, 2)$ |       |       |       |       |       |
|        |                           | oBIF       |      |       |       |       |       |
|        |                           | oBIF at $\sigma = 1$ | 529  | 40.00 | 47.50 | 68.75 | 79.58 |
|        |                           | oBIF at $\sigma = 2$ |       |       |       |       |       |
|        | Combined decision ($f_1, f_2$) |          |      | 63.75 | 75.42 | 87.50 | 96.67 |
| Task 5 | $f_1$                     | LBP        |      |       |       |       |       |
|        |                           | LBP at $(P, R) = (16, 4)$ | 14,337 | 36.25 | 45.00 | 61.25 | 72.50 |
|        |                           | LBP at $(P, R) = (8, 2)$ |       |       |       |       |       |
|        |                           | oBIF       |      |       |       |       |       |
|        |                           | oBIF at $\sigma = 1$ | 529  | 26.25 | 36.87 | 49.37 | 64.37 |
|        |                           | oBIF at $\sigma = 2$ |       |       |       |       |       |
|        | Combined decision ($f_1, f_2$) |          |      | 41.25 | 47.50 | 66.25 | 76.88 |
| Task 6 | $f_1$                     | LBP        |      |       |       |       |       |
|        |                           | LBP at $(P, R) = (16, 4)$ | 14,337 | 25    | 36.88 | 53.13 | 68.75 |
|        |                           | LBP at $(P, R) = (8, 2)$ |       |       |       |       |       |
|        |                           | oBIF       |      |       |       |       |       |
|        |                           | oBIF at $\sigma = 1$ | 529  | 24.37 | 33.75 | 47.50 | 64.37 |
|        |                           | oBIF at $\sigma = 2$ |       |       |       |       |       |
|        | Combined decision ($f_1, f_2$) |          |      | 31.88 | 45.00 | 61.25 | 75.63 |
proposed feature combination outperforms both these techniques indicating that ConvNets may not be able to learn robust feature representations due to the relatively limited amount of training data per class which is the case in most practical applications in the writer identification problem. For Task 3 (Arabic samples in training and French samples in test) and Task 4 (reverse of Task 3), it is observed that training on French samples and testing on Arabic samples (Task 4) report higher identification rates as compared with Task 3. For Top-1 identification rates, this pattern is consistent across all submitted systems with the exception of the ‘Tokyo’ system. Although for Top-2 to Top-10 identification rates, there are few inconsistencies in the performance of different systems, but in general, it can be observed that for most cases Task 4 identification rates are higher than those of Task 3 and the same is the case with our system.

Another important remark is related to the relatively low identification rates in Task 5 and Task 6 (WDAD dataset). It is observed that in these scenarios, the performance of other systems is also on the lower side indicating that the dataset might be more challenging and an enhanced feature set may be required to capture the writer-specific patterns across the two scripts. One possible reason could be the relatively less textual content in the writing samples as opposed to the CERUG

| Task   | System          | Classifier | Classification rates (%) |
|--------|-----------------|------------|--------------------------|
|        |                 |            | Top 1 | Top 2 | Top 5 | Top 10 |
| Task 1 | Proposed approach | SVM        | 63.75 | 75.00 | 86.25 | 95.00 |
|        |                  |            | 42.50 | 53.75 | 72.50 | 83.75 |
|        |                  |            | 57.50 | 67.50 | 80.00 | 86.25 |
|        | Tokyo           | KNN        | 23.75 | 42.50 | 60.00 | 68.75 |
|        | Nuremberg       | Cosine distance | 32.50 | 46.25 | 66.25 | 82.50 |
| Task 2 | Proposed approach | SVM        | 68.75 | 78.75 | 87.50 | 91.25 |
|        |                  |            | 56.25 | 70.00 | 81.25 | 90.00 |
|        |                  |            | 46.25 | 55.00 | 71.25 | 80.00 |
|        | Tokyo           | KNN        | 16.25 | 28.75 | 46.25 | 57.50 |
|        | Nuremberg       | Cosine distance | 27.50 | 40.00 | 61.25 | 80.00 |
| Task 3 | Proposed approach | SVM        | 50.42 | 65.83 | 79.17 | 86.25 |
|        |                  |            | 40.83 | 52.92 | 67.92 | 83.33 |
|        |                  |            | 37.50 | 50.00 | 68.75 | 80.83 |
|        | Tokyo           | KNN        | 16.25 | 28.75 | 46.25 | 57.50 |
|        | Nuremberg       | Cosine distance | 19.58 | 24.17 | 36.67 | 55.42 |
| Task 4 | Proposed approach | SVM        | 63.75 | 75.42 | 87.5  | 96.67 |
|        |                  |            | 42.08 | 51.67 | 73.83 | 85.00 |
|        |                  |            | 40.00 | 47.50 | 68.75 | 79.58 |
|        | Tokyo           | KNN        | 17.08 | 29.17 | 51.25 | 60.83 |
|        | Nuremberg       | Cosine distance | 31.25 | 36.67 | 46.67 | 63.75 |
| Task 5 | Proposed approach | SVM        | 41.25 | 47.50 | 66.25 | 76.88 |
|        |                  |            | 29.37 | 38.75 | 58.12 | 70.62 |
|        |                  |            | 26.25 | 36.87 | 49.37 | 64.37 |
|        | Tokyo           | KNN        | 09.37 | 16.87 | 31.25 | 50.62 |
|        | Nuremberg       | Cosine distance | 20.62 | 28.12 | 45.00 | 59.37 |
| Task 6 | Proposed approach | SVM        | 31.88 | 45.00 | 61.25 | 75.63 |
|        |                  |            | 28.75 | 38.12 | 59.37 | 68.75 |
|        |                  |            | 24.37 | 33.75 | 47.50 | 64.37 |
|        | Tokyo           | KNN        | 06.87 | 17.50 | 33.12 | 47.50 |
|        | Nuremberg       | Cosine distance | 17.50 | 21.87 | 38.75 | 51.87 |

TABLE 6 Performance comparison with systems submitted to the ICFHR 2018 competition.
(Task 1 and Task 2) and LAMIS-MSHD (Task 3 and Task 4) datasets. Furthermore, another important aspect is that although Top-1 identification rates are lower than 50% in these scenarios, the Top-10 identification rates are around 75% indicating that, to some extent, the common characteristics across multiple scripts are indeed captured by these features.

In addition to comparison with the systems submitted to ICFHR competition, similar to single-script experiments, we extracted a number of state-of-the-art features employed in different studies for writer identification. Features based on run length (f4–f6) [32], edge direction (f7) and edge hinge (f8) [51], chain codes (f9–f10) [21], delta hinge (f11) [52], COLD descriptor (f12) [53] and AR coefficients (f14) [10] are employed with an SVM classifier in the same experimental protocol as that of the competition. The corresponding identification rates for the six competition tasks have been

| Task | Features | Classification rates (%) | Classification rates (%) |
|------|----------|--------------------------|--------------------------|
|      |          | Top 1 | Top 2 | Top 5 | Top 10 | Top 1 | Top 2 | Top 5 | Top 10 |
| Proposed approach | 63.75 | 75.00 | 86.25 | 95.00 | 68.75 | 78.75 | 87.50 | 91.25 |
| f4   | 36.25 | 52.50 | 72.50 | 86.25 | 37.50 | 50.00 | 67.50 | 76.25 |
| f5   | 11.25 | 15.00 | 32.50 | 56.25 | 17.50 | 23.75 | 32.50 | 40.00 |
| f6   | 25.00 | 27.50 | 61.25 | 78.75 | 40.00 | 46.25 | 66.25 | 82.50 |
| f7   | 17.50 | 27.50 | 46.25 | 62.50 | 23.75 | 37.50 | 53.75 | 63.75 |
| Task 1 | f8 | 36.25 | 55.00 | 76.25 | 86.25 | 58.75 | 76.25 | 86.25 | 95.00 |
| f9   | 45.00 | 60.00 | 78.75 | 90.00 | 48.75 | 61.25 | 83.75 | 92.50 |
| f10  | 36.25 | 50.00 | 62.50 | 78.75 | 33.75 | 48.75 | 68.75 | 83.75 |
| f11  | 07.50 | 11.25 | 13.75 | 32.50 | 07.50 | 11.25 | 27.50 | 41.75 |
| f12  | 33.75 | 42.50 | 56.25 | 71.25 | 25.00 | 38.75 | 48.75 | 63.75 |
| f13  | 17.50 | 23.65 | 26.25 | 37.50 | 23.75 | 36.25 | 51.25 | 67.50 |
| Proposed approach | 50.42 | 65.83 | 79.17 | 86.25 | 63.75 | 75.42 | 87.50 | 96.67 |
| f4   | 18.75 | 31.25 | 54.17 | 77.06 | 33.33 | 48.75 | 69.58 | 83.33 |
| f5   | 18.75 | 30.00 | 55.00 | 72.08 | 38.33 | 49.58 | 65.00 | 76.25 |
| f6   | 31.67 | 47.92 | 72.92 | 83.75 | 49.17 | 59.58 | 74.14 | 84.58 |
| f7   | 14.58 | 19.58 | 33.33 | 50.42 | 11.25 | 19.17 | 32.08 | 40.42 |
| Task 3 | f8 | 33.75 | 43.33 | 57.70 | 68.33 | 39.17 | 45.83 | 67.50 | 75.83 |
| f9   | 23.33 | 33.75 | 58.75 | 76.67 | 37.50 | 47.92 | 57.08 | 66.67 |
| f10  | 22.50 | 33.75 | 53.33 | 67.50 | 39.17 | 51.25 | 62.92 | 73.33 |
| f11  | 04.17 | 05.83 | 12.92 | 25.42 | 06.67 | 9.58 | 15.42 | 26.67 |
| f12  | 06.67 | 12.50 | 22.50 | 40.00 | 08.33 | 10.83 | 19.17 | 36.67 |
| f13  | 15.83 | 20.83 | 42.08 | 59.58 | 27.50 | 38.33 | 50.83 | 57.08 |
| Proposed approach | 41.25 | 47.50 | 66.25 | 76.88 | 31.88 | 45.00 | 61.25 | 75.63 |
| f4   | 20.00 | 26.88 | 45.63 | 61.88 | 19.38 | 26.88 | 46.25 | 62.50 |
| f5   | 08.13 | 10.00 | 20.00 | 36.25 | 11.25 | 17.50 | 30.63 | 43.75 |
| f6   | 21.25 | 28.13 | 47.50 | 62.50 | 27.50 | 36.88 | 55.63 | 69.83 |
| f7   | 08.75 | 14.38 | 28.13 | 45.00 | 10.63 | 20.00 | 30.00 | 40.63 |
| Task 5 | f8 | 26.25 | 34.38 | 51.25 | 66.25 | 31.25 | 41.88 | 64.38 | 76.25 |
| f9   | 26.50 | 35.63 | 48.75 | 49.38 | 21.88 | 26.88 | 41.25 | 60.63 |
| f10  | 18.75 | 26.25 | 42.50 | 56.20 | 17.50 | 23.75 | 40.00 | 52.50 |
| f11  | 04.38 | 07.50 | 14.38 | 20.63 | 10.00 | 11.86 | 18.75 | 33.75 |
| f12  | 10.63 | 15.63 | 33.13 | 46.25 | 09.38 | 15.00 | 28.13 | 42.50 |
| f14  | 08.16 | 13.75 | 26.25 | 43.13 | 11.25 | 18.13 | 26.88 | 35.00 |
summarised in Table 7 where it can be seen that the proposed feature set outperforms all other features in Top-1 identification rates on all six tasks. Likewise, with few exceptions, the highest Top-2 to Top-10 identification rates are also reported by the LBP and oBIFs combination proposed in the current study. As discussed earlier, multi-script writer identification is much more challenging when compared with the conventional single-script scenario. Naturally, the performance of the LBP and oBIFs column histograms on single-script evaluations (Table 3) outperforms those in multi-script evaluations. For multi-script experiments, in many cases, a Top-1 identification rate of more than 60% is reported, while the Top-10 identification rates are more than 75% for all tasks. Considering the difficulty of the problem, the obtained classification rates are indeed very promising. Another interesting observation is that the employed features report more or less consistent performance for diverse scripts and are hence not linked to a particular script. In other words, features characterising the writer are transferred from one script to another and our findings are similar to those reported in Ref. [55]. Few samples illustrating correct identification of writers in a multi-script scenario are presented in Figure 10.

6 | CONCLUSION

This article investigated the effectiveness of texture feature column scheme to characterise writer from handwriting. Different configurations of the LBP column histogram and the oBIFs column histogram are investigated with an SVM classifier. Evaluations are carried out on two datasets in the single-script and three datasets in a multi-script experimental protocol and the performance is compared with the recent studies reported in the literature.

An important aspect of this study was the investigation of common characteristics across multiple scripts produced by the same individual. The reported results validate the hypothesis that individuals do share writer-specific features in different scripts and textural measures can effectively capture this information. This not only represents an interesting problem in basic research but can also be very beneficial in the development of semi-automated tools for forensic experts. Such tools can help in narrowing down the search space against a questioned handwriting.

In our subsequent study on this subject, we plan to study the effectiveness of the employed column schemes in predicting demographic attributes of writers in addition to identity. LBP and oBIFs column features can be complemented by other textural descriptors and a comprehensive feature selection study can be carried out to investigate the optimal set of textural features for this problem. In addition to handwriting, we also intend to study the robustness of these features for signature verification and other related problems.

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