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Local binary pattern and its derivatives to handwriting-based gender classification

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ABSTRACT

Several studies by psychologists and computer scientists have verified the link between handwriting and writer gender. The texture of the writing image is a major indicator of whether it is male or female writing. This paper conducts a comparison analysis to examine the effectiveness of various local binary patterns (LBPs) techniques in detecting gender from scanned images of handwriting. We study different LBP variants, including complete local binary pattern (CLBP), local ternary pattern (LTP), local configuration pattern (LCP), rotated local binary pattern (RLBP), local binary pattern variance (LBPV), and multi-scale local binary pattern (MLBP), as features for representing handwriting images. A support vector machine (SVM) is trained using features from male and female writing. The method achieves encouraging classification rates of 76.68 when tested on subsets of the Qatar University writer identification (QUWI) dataset containing English and Arabic writing samples when using the experimental protocols of the International Conference on Document Analysis and Recognition (ICDAR) 2013 gender classification competitions.

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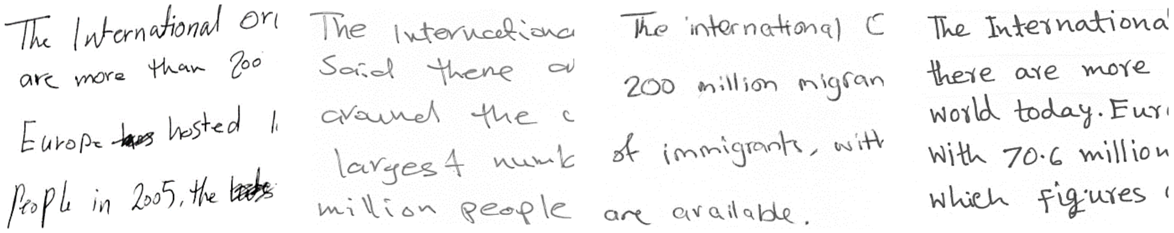
1. INTRODUCTION

The history of handwriting is rich and long. After advancing from pictorial communication, civilizations created handwriting, employing abstract symbols and letters to represent thoughts. Unlike printed writing, which just carries the content, handwriting also contains information about the author. Because every person has a different writing style, handwriting can be used as an effective biometric modality, leading to systems for writer/signature identification and verification [1], [2]. Similarly, handwriting has been used to describe many personalities [3], demographic [4], [5], and characteristics of writers [6]. The classification of demographic features is objective and may be scientifically tested, whereas personality profiles are subjective. As a result, some research [4]–[8] have looked into the relationship between a person's handwriting and characteristics including gender, age, race, and handedness. The most extensively researched of these is gender prediction of gender based on handwriting, which is also the focus of the study we are presenting.

According to psychologists [9]–[11], differences in motor coordination between male and female writers explain for differences in their writing styles. Although psychologists and neurologists have long researched the relationship between gender and handwriting, it has only been in the last ten years that the pattern classification community has focused on computerized analysis of handwriting to determine the writer's gender. In order to train a learning algorithm to distinguish between male and female writers, features taken from examples of both genders' writing are typically supplied into the algorithm. These features, which may be calculated algorithmically, are a subset of the features recognized by psychologists [10], [11]. Male writings are typically rushed and spiky, while feminine writings are typically more uniform and decorative [10], [11]. Figure 1 provides examples of male and female writers' handwriting to substantiate these observations, where we find Figure 1(a) representing an example of the writing of the male writer and Figure 1(b) showing an example of the writing of the female writer.



(a) (b)

Figure 1. Samples of: (a) male and (b) female writings

It should be mentioned that the identification of writers and the prediction of gender are linked issue areas. In order to identify a writer, distinctive qualities that best reflect their writing style are looked after. On the other side, gender classification aims to characterize both female and male gender classes in more basic terms. Despite being a two-class classification issue, gender classification based on handwriting is extremely difficult because many male writers tend to be feminists, and vice versa, leading to a high level of inter-class resemblance.

The work Bandi and Srihari [6] investigate a number of macro and micro handwriting features by using artificial neural network (ANN) combined with bagging and boosting techniques to categories writers into various demographic groups is one of the most notable contributions to the classification of gender from handwriting. To identify gender and handedness (left or right) from handwriting, Liwicki *et al.* [5] retrieved a collection of offline and online features from handwriting. Support vector machine (SVM) and gaussian mixture models classified 200 writers from the IAM-on dataset with classification rates for gender and handedness of 67% and 85%, respectively [12]. According to Siddiqi *et al.* [8], writers use a mix of features related to orientation and curvature to categorize gender from handwriting. An analysis of 300 writers in the Qatar University writer identification (QUWI) dataset found that the average classification accuracy was about 68%. From handwriting, Maadeed and Hassaine [13] use a collection of geometrical characteristics to deduce gender, age, and handedness. In an experimental investigation using the QUWI dataset in text-dependent and text-independent approaches, kernel discriminant analysis and random forests were employed to classify data, with the greatest classification rate being 74%. Similarly, to classify gender from online handwriting, a set of local descriptors utilizing histogram of local binary patterns (LBPs), histogram oriented gradients (HOG), and pixel density are utilized with SVM classifier. On 200 writers, the system reports a 74% accuracy rate [7]. To characterize the gender of the writer, Youssef *et al.* [14] propose using gradient-based features to learn the SVM for English writings and wavelet domain local binary patterns (WDLBP) to train the SVM for Arabic writings. By breaking down a textured image into a number of wavelet sub-bands at various levels, Akbari *et al.* [15] proposed to detect gender from a writer's handwriting. These series were then extended into data sequences, which were then built into probabilistic finite state automata (PFSA) that produces vectors of features. ANN and SVM used to classify these features. Three subsets of the QUWI dataset are used to evaluate the system, and the results show the best prediction rates. Recently, Gattal *et al.* [16] propose to combine of oriented basic image features (oBIFs) columns histograms and different configurations of oBIFs extracted from writing samples to learn an SVM. The system is evaluated on three parts of the QUWI dataset and report best classification rates. A new method based on hinge feature and cloud of line distribution (COLD) is proposed by Gattal *et al.* [17] to be used to identify the gender from handwriting. A number of studies mentioned in [18]–[20] validated the relationship between gender and handwriting. In these studies, a comparative analysis of the mentioned methods of feature extraction and classification, as well as the accessible datasets, is also presented. Finally, Maken and Gupta [21] proposed a new method for the gender classification system based on offline handwriting using slanteness, area, and perimeter. For classification, the SVM with logistic regression and k-nearest neighbours (KNN) was used, yielding interesting results.

As previously mentioned, the handwriting gender classification challenge has been approached using a variety of machine learning techniques. Feature extraction and classifier training are the main foundations of these techniques. The literature research demonstrated that machine learning and deep learning methods had been successfully employed for classifying a writer's demographics [16]–[18], [22]. Despite their effectiveness, a fundamental problem in these deep learning-based systems is the availability of massive training data sets and powerful computing resources. Moreover, these models require fixed-sized images, which can distort the structure of a word in exceptional cases.

The QUWI dataset has been used to hold a number of gender detection competitions [23]–[25]. Here, we focused on making comparisons with the techniques used on subsets of the QUWI dataset in contests of the International Conference on Document Analysis and Recognition (ICDAR) 2013 [23] based on various assessment modes. Each participant in the ICDAR 2013 contest received a set of more than 30 attributes that were taken from all the handwriting samples. Each participant supplied a probability value for each writer in the test set, showing the likelihood that the writer is male. The participating system by "AnilThomas" [23], who employed a feature selection technique utilizing gradient boosting decision trees (GBDT), won the ICDAR 2013 contest. The first 80 features were chosen for further regressions after ranking the features in descending order of relevance. Using a gradient boosting machine classifier, these most discriminating features were learned separately on English and Arabic handwritings.

The classification of gender is more accurate when based on the overall visual look of the writing rather than the more traditional characteristics of handwriting, which are more closely related to personality traits [3]. These characteristics include the slopes of the lines, word spacing, characters, page margins, pen pressure, and degree of cursiveness. The gender of the writer can be accurately predicted from a particular writing sample by using texture-based metrics, which treat each writing image as a texture.

The main steps in the standard design process for a handwriting-based gender identification system are preprocessing, feature extraction, and classification. All the operations required to create the cleaned-up version of the image are included in the preparation stage. Binarization, smoothing, and filtering processes are all included. The various LBPs and its derivatives LBP, complete local binary pattern (CLBP), local ternary patterns (LTP), local configuration patterns (LCP), rotated local binary pattern (RLBP), local binary pattern variance (LBPV), and multi-scale local binary pattern (MLBP)) are applied in order to extract features from the binarized handwriting images. The SVM is used to classify the normalized feature vector into the male or female class. A summary of the suggested approach is shown in Figure 2.

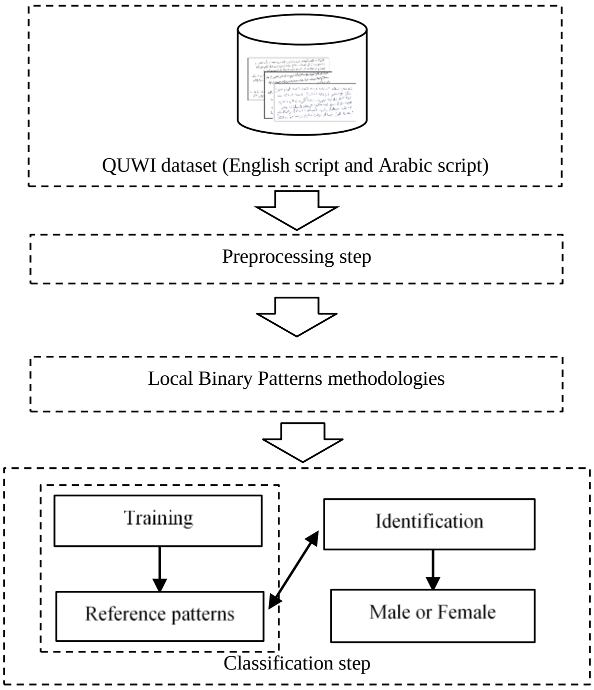


Figure 2. Steps in the proposed approach

One of the main challenges in pattern recognition is texture classification, which has been explored for many years [26]–[31]. To describe and match textured images, statistical [25]–[29] and structural

[25], [26] methods have been used. This study uses statistical textural metrics to categorize writers' gender from scanned images of their handwriting. The gender can be determined from handwriting using LBPs [32], [33] and its derivatives. These include LTP [34], LCP [35], CLBP [36], RLBP [37], LBPV [38], and MLBP [39]. The main goal of this study is to identify the most effective textural measures for characterizing gender from handwriting.

The remainder of the paper is structured as follows. We start by outlining the dataset we used for this research in section 2. Each of the textural measures employed in our study is briefly described in section 3. Section 4 contains the classification methodology while section 5 provides details on the experimental results and their interpretation, whereas. Section 6 concludes the paper with some insightful suggestions for further research on this issue.

2. DATASET

For the experimental evaluation of the system, a part of the QUWI dataset is used [24]. Each contributor to the dataset, who totals more than 1,000, has contributed four writing samples, two in English and two in Arabic. On a single page, each writer submitted an arbitrary text in both English and Arabic along with the identical text in English (Arabic). This dataset is available publicly in part. The writing samples from the QUWI dataset used in the ICDAR 2013 contest total 475 writers (221 male and 254 female), of which 282 writers (564 English and 564 Arabic handwriting samples) and 193 writers (386 English and 386 Arabic handwriting samples) are employed in our studies. Following is the distribution of writers and samples in the QUWI dataset used in the ICDAR 2013 contest for gender classification: i) overall number of writers is 475; ii) overall number of training set is 282; iii) overall number of test set is 193; iv) gender: male (221) and female (254); and v) number of samples/writers is 4 (2 Arabic and 2 English).

3. FEATURE EXTRACTION

The primary goal of the handwriting preprocessing phase is to eliminate any noise or distortions that may be present in the document. The specific textural elements that we extract from each handwriting image are described in this section. Following provides an overview of the features that make up LBPs and its derivatives. The proposed method uses MLBP calculated from preprocessed handwriting images. The classification is then performed using an SVM, which allows the normalized feature vector to be assigned to either the male or female class. Figure 3 depicts an overview of the proposed strategy.

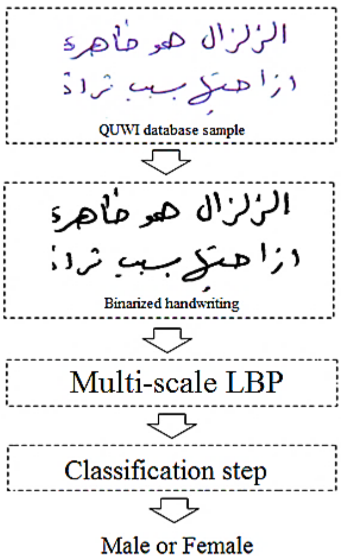


Figure 3. Structure of the proposed method

3.1. Local binary patterns

Ojala *et al.* [32], first proposed LBPs for rotation-invariant texture categorization. LBP is an effective textural descriptor that has been used to solve several classification issues. From a calculation standpoint, it takes into account the immediate neighborhood surrounding each pixel and compares the intensity level of neighbors with the core pixel. All neighbors with an intensity value equal to or greater than the value of the center pixel is given a value of 1. A 0 is assigned to pixels whose values are less than those of the center pixels. The generated series of zeros and ones is then treated as a binary number, and its decimal counterpart is calculated.

$$LBP_{P,R} = \sum_{P=0}^{P-1} 2^P s(i_P - i_c) \quad \text{where} \quad \begin{Bmatrix} s(x) = 0, x < 0 \\ s(x) = 1, x \geq 0 \end{Bmatrix} \tag{1}$$

Where P denotes the number of nearby pixels, i_P stands for the neighboring pixel's grayscale, and i_c stands for the central pixel's grayscale. An illustration of LBP computation is shown in Figure 4.

181	173	132
186	**178**	154
186	192	145

Binary number: 10000111

1	0	0
1		0
1	1	0

Decimal: 135

Figure 4. LBP computation example

3.2. Complete local binary pattern

LBPs are the only ones to account for the local structure of the image, ignoring the size difference between the core pixel and its surrounding pixels. According to Guo *et al.* [36], LBP frequently tends to produce inconsistent codes since it simply takes into account the difference between two gray values, as shown in Figure 5. The figure displays the binary code produced by the LBP operator for the center pixel with the intensity value (49). In this instance, the generated LPB code represents a false dark spot. Figure 5 provides examples of inconsistent binary pattern in the LBP encoding process.

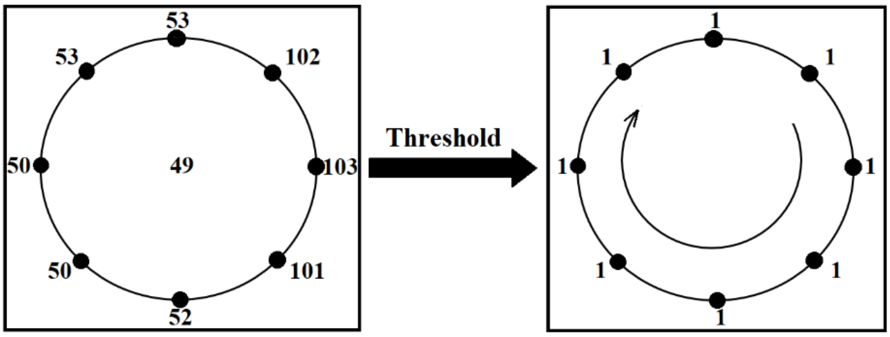


Figure 5. Inconsistent LBP

Guo *et al.* [36] developed a complete LBP model named CLBP to address this issue. The local variances in magnitude and information regarding each pattern's sign were integrated with the center grayscale data. To capture the sign and magnitude of the change, two bits are used. In (2) provides a summary of the computation:

$$s_P = s(i_P - i_c), \quad m_P = |i_P - i_c| \tag{2}$$

where i_p is the intensity level of the nearest pixel, i_c is the intensity level of the center pixel, s_p is the sign difference between the central and neighboring intensity levels, and m_p is the magnitude difference. Additionally, CLBP-sign ($CLBP\_S$) and CLBP-magnitude ($CLBP\_M$) are computed using s_P and m_P. In (3) and (4) are used, respectively, to mathematically express $CLBP\_S$ and $CLBP\_M$:

$$CLBP\_S_{P,R} = \sum_{P=0}^{P-1} 2^P s(i_P - i_c), \quad \begin{Bmatrix} s_P = 0, i_P < i_c \\ s_P = 1, i_P \geq i_c \end{Bmatrix} \tag{3}$$

$$CLBP\_M_{P,R} = \sum_{P=0}^{P-1} 2^P t(m_P, c), \quad \begin{Bmatrix} t(m_P, \mathrm{c}) = 1, |i_P - i_c| \geq c \\ \mathrm{t}(m_P, \mathrm{c}) = 0, |i_P - i_c| < c \end{Bmatrix} \tag{4}$$

where i_P represents the intensity level of neighboring pixel, i_c represents the intensity level of center pixel, R is the radius of neighborhood and P is the value of center pixel. Guo *et al.* [36], further introduced a new operator called CLBP center (CLBP C) that uses the gray level of each pattern (5):

$$CLBP\_C_{P,R} = t(i_c, c_i) \tag{5}$$

The Figure 6 results of CLPB computation. From the 3×3 image block (see Figure 6(a)), the local differences are extracted (see Figure 6(b)) for the purpose of dividing CLPB into two complimentary components, the sign component (see Figure 6(c)) and the magnitude component (see Figure 6(d)). Figure 6 shows the results of the CLPB computation. The CLPB separates the extracted local differences (see Figure 6(b)) from the 3×3 image block (see Figure 6(a)) into two complementary components, the sign component (see Figure 6(c)) and the magnitude component (see Figure 6(d)).

9	12	34
10	**25**	28
99	64	56

(a)

-16	-13	9
-15		3
74	39	31

(b)

-1	-1	1
-1		1
1	1	1

(c)

16	13	9
15		3
74	39	31

(d)

Figure 6. Computation of CLPB; (a) pattern of 3×3 blocks, (b) local differences, (c) sign component, and (d) magnitude component

3.3. Local ternary pattern

Tan and Tiggs [34] proposed the LTP descriptor. The authors added three values (-1, 0, 1) to the two-valued (0, 1) LBP codes. As seen in (6), LTP uses a threshold to divide nearby pixels into three values rather than threshold values of 0 and 1.

$$\mathrm{LTP_{P,R}} = \sum_{\mathrm{P}=0}^{\mathrm{P}-1} 2^{\mathrm{P}} \mathrm{s}(\mathrm{i_P} - \mathrm{i_c}), \quad \begin{Bmatrix} \mathrm{s(x)} = 1, & \mathrm{x} \geq \mathrm{t} \\ \mathrm{s(x)} = 0, & -\mathrm{t} < \mathrm{x} < \mathrm{t} \\ \mathrm{s(x)} = -1, & \mathrm{x} < -\mathrm{t} \end{Bmatrix} \tag{6}$$

The higher and lower threshold values are set to $x + t$ and $x - t$, respectively, with t representing the threshold value, and x representing the value of the center pixel. Neighboring pixels with values in this range are given the value 0. The neighboring pixels with values above the higher threshold are given a value of 1, and the remaining pixels with values below the lower threshold are given a value of -1. The higher and lower patterns are subsequently constructed independently for each pixel. -1 values are changed to 0 for the top pattern, while 1 value is changed to 0 for the lower pattern. The combination of the higher and lower patterns is the last LTP operator. Figure 7 depicts an illustration of an LTP operator with a threshold value of 5. The 3×3 image block that is shown in Figure 7(a) is from which the ternary pattern (represented in Figure 7(b)) is produced, which is also coded into higher (shown in Figure 7(c)) and lower binary patterns (shown in Figure 7(d)).

32	92	103
71	**35**	21
13	34	10

(a)

0	1	1
1		-1
-1	0	-1

(b)

0	0	0
0		1
1	0	1

(c)

0	1	1
1		0
0	0	0

(d)

Figure 7. Computation of LTP; (a) pattern of 3×3 blocks, (b) ternary pattern, (c) higher pattern, and (d) lower pattern

3.4. Local configuration patterns

Guo *et al.* [35] suggested the LCP, another variation of the LBP, to extract the structural and microscopic configuration features in the image. Figure 8 demonstrates how LCP differs from conventional LBP and what motivates it. Figures 8(a) and 8(b) for image samples show the same design but distinct textures. Local variation information may be used to solve the issue, but if we look at Figures 8(b) and 8(c), we can see that, although having different settings, they also produce the same code.

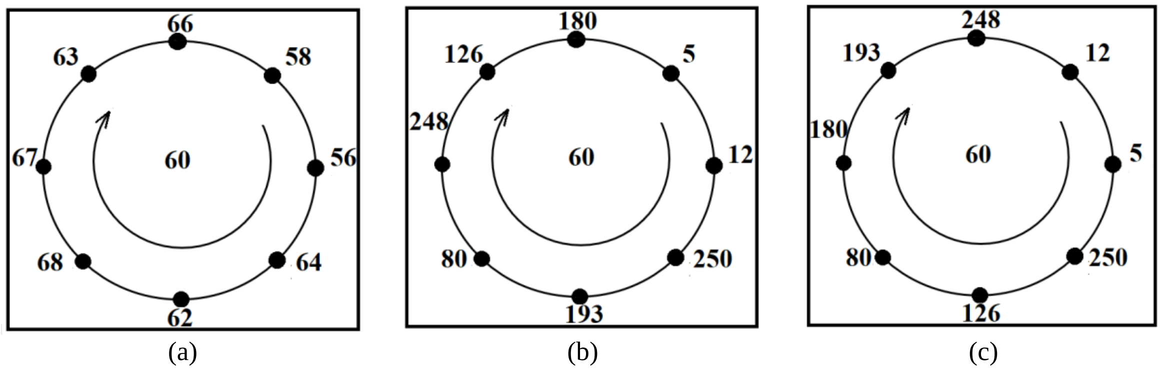


Figure 8. Problems with LBP; (a) low density pattern, (b) height density pattern, and (c) height density pattern using a different setting

Research by Guo *et al.* [35], model the microscopic information of each pattern and compute the appropriate weight associated with the intensity of nearby pixels to address the problems with LBP. In (7) represents the model numerically:

$$E(a_0 , \dots , a_{p-1}) = |g_c - \sum_{i=1}^{p-1}(a_i g_i)| \tag{7}$$

where a_i is the weighting parameter, the intensity value of the central pixel is denoted by g_c, while the intensity value of neighboring pixel is denoted by g_i.

3.5. Rotated local binary pattern

By employing the magnitude information retrieved by LBP, it is suggested that RLBP can capture the entire structural information as well as complementary information [38]. By rotating the weights with regard to predominate direction, this descriptor is calculated [37]. Since the dominating direction (D) in the circular neighborhood is used as the reference, it is defined as (8):

$$D = arg\ max\ |i_P - i_c| \tag{8}$$

Hence, the RLBP operator is described as (9):

$$RLBP_{P,R} = \sum_{p=0}^{p-1} 2^{mod(P-D,P)}\ s(i_P - i_c) \tag{9}$$

The weights are moved in a circular manner with respect to the dominant direction.

3.6. Local binary pattern variance

LBPV has been presented [38] as a way of incorporating the local contrast complementary information into the one-dimensional LBP histogram. The threshold values from the test images are quantized using a rotation-invariant measure of the local variance (VAR) calculated by summing the distributions of feature over all learning images. It is described as (10):

$$VAR_{P,R} = \frac{1}{P}\sum_{P=0}^{P-1}(i_P - u)^2 \qquad \text{Where,} \qquad u = \frac{1}{p}\sum_{p=0}^{p-1} i_p \tag{10}$$

Several threshold values are generated to divide the overall distribution into N bins with equal entry numbers. The LBPV is a simple but effective combination of LBP and methods of contrast distribution. As a result, the variance VAR can be adopted as an adaptive weight to modify the LBP code contribution to the histogram calculation. In addition, LBPV is entirely training-free and does not require any quantization. To calculate the LBPV histogram:

$$\mathrm{LBPV}_{P,R}(k) = \sum_{i=1}^{N} \sum_{j=0}^{M} w(\mathrm{LBP}_{P,R}(i,j),k) \ , k \in [0,k] \quad (11)$$

where:

$$w\left(\mathrm{LBP}_{P,R}(i,j),k\right) = \begin{cases} \mathrm{VAR}_{P,R}(i,j), & \mathrm{LBP}_{P,R}(i,j) = k \\ 0 & \text{otherwise} \end{cases} \quad (12)$$

3.7. Multi-scale local binary pattern

Using a MLBP, which takes advantage of the multi-resolution data gleaned from the regional histogram, frequently improves the discrimination power of the resulting features [39], even if the LBP at different radii is typically not statistically independent. By combining the LBP images and changing the sample radius (R), MLBP can be produced. It shown that it was more accurate than the single scale LBP feature. The MLBP approach can typically be implemented using image interpolation or low-pass filtering by extending the radius of the LBP operator while maintaining lobe size constant. To eliminate handwriting jitter, low-pass filters must be used to smooth the input handwriting. A moving window operator, which changes the value of each pixel in an image one at a time using a window as a local region of pixels, is commonly used in low-pass filters. To affect every pixel in the image, the operator slides over it. In this instance, high spatial frequency noise in the handwriting is reduced using a gaussian low pass filter with a filter size value equal to ceil (abs(6*sigma+1)) and sigma=0.5. Consequently, by applying a variety of LBP operations to an image and merging the results. In our implementation, we extract the seven textural measurements LBP, CLBP, LTP, LCP, RLBP, LBPV, and MLBP from each of the handwriting images. The histogram of the textural descriptors computed from each image is used as a descriptor.

4. CLASSIFICATION

In this paper, a classifier is introduced to characterize male and female writings in variable writing styles. Features for the classification are produced based on the texture-based metrics like LBP, LTP, CLBP, LCP, RLBP, LBPV, and MLBP. A classifier needs to be trained using the features extracted from samples of female and male writings. In this investigation, we have chosen to employ an SVM classifier [40] that constructs two binary classifiers in order to deal with the two-class problem. Both binary classifiers have been taught to distinguish between the two classes. The SVMs classifier receives the texture feature vector from the query handwriting image and predicts the class label, male or female, by picking the maximum value of two SVMs. SVM performance is influenced by the the soft margin parameter C, kernel selection type, and kernel parameters. In our instance, the parameter C is picked fixed at 10 and the radial basis function (RBF) kernel parameter (σ) is chosen in the range=[1:100], allowing for a higher identification rate.

5. RESULTS AND DISCUSSION

Experiments with SVM that use intermediate textural measure results as a function of LBP descriptor parameters like radius (R) and number of neighbors (P) are adjusted to improve their validity. Male and female writers in Arabic and English are represented in the training and test sets of these experiments. The ICDAR 2013 dataset's training set includes 1,128 Arabic and English samples collected from 282 writers. Similarly, the test set is created by merging 772 Arabic and English samples from 193 writers. The purpose of these experiments is to investigate the mpact of textural metrics while applying optimal parameters to compute various LBP variations. Table 1, reports the textural measures based on LBPs and their derivatives on male, female, and overall overall classification rates from complete binarized images.

The LBP, LTP, RLBP, and LBPV descriptors achieve a classification rates on all Arabic and English samples of 73.58%, 72.02%, 71.63%, and 73.45%, respectively, as shown in Table 1. Better classification rates are reported by the uniform CLBP and MLBP, which are 73.70% and 76.03%, respectively. But out of all the descriptors, LCP has the lowest classification rate. Among the textural descriptors, the MLBP textural descriptor is the most successful in identifying the gender of writers from handwriting images. The parameters of SVM were empirically tuned to C=10 and σ=19.

In order to increase the classification rate, we additionally evaluated the MLBP descriptor (uniform $\mathrm{MLBP}_{8,\ [2,4,8,16]}$) with SVM classifier using the complete image (CI) and also from various regions in the image by applying uniform grid sampling (UGS) [41]. A uniform grid generates rectangular sampling zones that are all the same size and shape. The resultant vector is normalized to have a zero mean and unit variance. The classification results on the uniform MLBP using the uniform grid approach are summarized in Table 2. When the uniform MLBP is extracted from both the complete image and its 2×3 grid, generating a feature vector with a dimension of 6,608, the highest classification rate of 76.68% is achieved.

Table 1. Gender classification results on the QUWI dataset along seven textural measures with optimal parameters

Description of the feature histogram	Feature parameters	Dimension	Classification rates (%)		
			Male	Female	All
Uniform $LBP_{16,4}$	R=4 and P=16	243	76.52	71.40	73.58
Uniform $CLBP_{8,2}$	R=4 and P=16	118	72.87	74.32	73.70
LTP	Threshold=0.5	512	73.78	70.72	72.02
Uniform $LCP_{2,8}$	R=2 and P=8	81	58.84	66.22	63.08
Uniform $RLBP_{8,4}$	R=4 and P=8	59	74.39	69.59	71.63
Uniform $LBPV_{16,4}$	R=4 and P=16	243	78.66	69.59	73.45
Uniform $MLBP_{8,R}$	R=[2,4,8,16] and P=8	944	81.40	71.17	76.03

Table 2. Classification results on the uniform MLBP using uniform grid method

Uniform $MLBP_{8,[2,4,8,16]}$		Dimension	Classification rates (%)		
Using CI	Using UGS		Male	Female	All
No	1×2 grid	1,888	82.32	71.85	76.30
	2×1 grid	1,888	82.93	69.59	75.26
	2×2 grid	3,776	82.62	70.27	75.52
	2×3 grid	5,664	83.54	71.40	76.55
	3×2 grid	5,664	79.88	69.82	74.09
	3×3 grid	8,496	80.18	71.40	75.13
Yes	1×2 grid	2,832	78.66	73.20	75.52
	2×1 grid	2,832	82.01	70.72	75.52
	2×2 grid	4,720	82.32	71.85	76.30
	2×3 grid	6,608	82.01	74.10	76.68
	3×2 grid	6,608	80.79	70.27	74.74
	3×3 grid	9,440	80.18	72.75	75.91

Additionally, we chose the QUWI dataset used in the ICDAR 2013 competition on all Arabic and English samples to compare our proposed approach against various state-of-the-art methods in gender classification. These comprise a number of methods mentioned in section 1. However, Table 3 provides an overview of the gender classification rates on the QWUI dataset as well as the results from some recent research on the same topic.

Table 3. Classification rates on the ICDAR 2013 datasets

Method	Script		Classification method	Classification rates (%)
	Train	Test		
Wavelet [15]	English and Arabic	English and Arabic	NN	79.30
oBIFs [16]	English and Arabic	English and Arabic	SVM	76.17
Winning system in ICDAR 2013 contest [23]	English and Arabic	English and Arabic	GBDT	76.00
ICDAR 2013 features [13]	English and Arabic	English and Arabic	SVM	75.20
Gradient-based features and WDLBP [14]	English and Arabic	English and Arabic	SVM	74.30
Orientation and curvature features [8]	English and Arabic	English and Arabic	SVM	68.75
Proposed method using UGS	English and Arabic	English and Arabic	SVM	76.68
Proposed method without UGS	English and Arabic	English and Arabic	SVM	76.03

The classification rate for the proposed method is greater than 76%. In general, the proposed approach is better suitable for gender classification. When we compare the proposed method to other gender classification approaches described in the literature, we can see that it achieves a classification rate similar to that of Akbari *et al.* [15] and Gattal *et al.* [16]. However, compared to the proposed method, their approach is significantly slower and requires more preprocessing steps and feature extraction processes. Subsequently, we present the proposed system performance with optimal feature on all samples in English and Arabic in script-dependent and script-independent evaluation modes.

5.1. Script-dependent evaluation mode

The script-dependent evaluations for pages 1 and 2 in Arabic then pages 3 and 4 in English are carried out separately in the training and test sets of the ICDAR 2013 contest process. Instead, the test set has samples from 193 writers, while the training set comprises samples from 282 writers. Therefore, Table 4 provides an overview of the outcomes of the proposed approach using various approaches to the gender identification problem in script-dependent evaluation mode.

Table 4 shows that the proposed strategy obtains higher average classification rates of 76.94 in the identical experimental settings as ICDAR 2013 contests. Roughly speaking, the proposed method is more suited for script-dependent gender classification. We can also see that the proposed approach delivers an average rate that is comparable to that of the method proposed by Youssef *et al.* [14]. However, their method uses two different features: gradient-based features for English writings and WDLBP for Arabic writings. As a result, their outcomes are inconsistent.

Table 4. Classification results of script-dependent evaluations on ICDAR 2013 datasets

Method	Script Train	Script Test	Classification method	Classification rates(%) Script-dependent	Average
Gradient-based features and WDLBP [14]	Arabic	Arabic	SVM	68.60	77.15
	English	English		85.70	
oBIFs [16]	Arabic	Arabic	SVM	76.17	77.07
	English	English		77.98	
Wavelet [15]	Arabic	Arabic	SVM	77.70	76.60
	English	English		75.50	
ICDAR 2013 features [13]	Arabic	Arabic	SVM	62.30	69.70
	English	English		77.10	
Orientation and curvature features [8]	Arabic	Arabic	SVM	68.50	68.50
	English	English		68.50	
Proposed method using UGS	Arabic	Arabic	SVM	72.54	75.65
	English	English		78.76	
Proposed method without UGS	Arabic	Arabic	SVM	75.65	76.94
	English	English		78.24	

5.2. Script-independent evaluation mode

In the script-independent mode, samples from one script are included in the training set while samples from the other script are included in the test set. This is done in according the ICDAR 2013 contest protocol. As a result, the training set for these experiments includes samples from 282 Arabic writers, while the test set includes samples from 193 English writers. Thus, the comparative script-independent evaluation works well with our method. Table 5 displays the gender classification rates in the script-dependent mode.

In the script-independent mode, samples from one script are included in the training set, while samples from the other script are included in the test set. This is done according to the ICDAR 2013 contest protocol. As a result, the training set for these experiments includes samples from 282 Arabic writers, while the test set includes samples from 193 English writers. Thus, the comparative script-independent evaluation works well with our method. Table 5 displays the gender classification rates in the script-dependent evaluation mode.

The classification rates in Table 5 show that the proposed approach surpassed other methods in the literature in terms of the average performance of the script-independent evaluations. The average classification rate for ICDAR 2013 contests is 72.80. We clearly see that the proposed approach outperforms other approaches in the most challenging setting of script-independence, where other approaches report rather low average classification rates. The investigation of system performance in both text-dependent and text-independent modes is then presented.

Table 5. Classification results in script-independent mode on the ICDAR 2013 datasets

Method	Script Train	Script Test	Classification method	Classification rates (%) Script-independent	Average
oBIFs [16]	Arabic	English	SVM	73.32	71.37
	English	Arabic		69.43	
Wavelet [15]	Arabic	English	SVM	69.40	69.00
	English	Arabic		68.60	
Orientation and curvature features [8]	Arabic	English	NN	65.00	65.00
	English	Arabic		65.00	
Proposed method using UGS	Arabic	English	SVM	72.80	70.72
	English	Arabic		68.65	
Proposed method without UGS	Arabic	English	SVM	72.80	70.72
	English	Arabic		68.65	

5.3. Text-dependent and text-independent evaluation mode

The purpose of these experiments is to see how system performance changes depending on the textual content of the writing samples and to examine writing samples with various types of text. For text-dependent evaluations, page 2 in Arabic and page 4 in English for each person contain the similar text. Consequently, only the pages of all writers that contain random text, page 1 in Arabic and page 3 in English, are used. The outcomes of these experiments are shown in Table 6, along with those of comparable evaluations that have been available in the literature. The results produced by the text-dependent and text-independent modes are often similar and superior to those reported in the literature. When the textual content is in the same script, the realized classification rates in learning and testing samples are higher than those reached with Arabic scripts. The proposed system outperforms existing approaches in these investigations as well, with the exception of one experiment on English script published by Akbari *et al.* [15].

Table 6. Text-dependent and text-independent classification rates on the ICDAR 2013 datasets

Method	Script		Classification method	Classification rates (%)		
	Train	Test		Text-dependent	Text-independent	Average
Wavelet [15]	Arabic	Arabic	SVM	76.20	74.20	75.20
	English	English	SVM	75.20	76.10	75,65
Geometric features [13]	Arabic	Arabic	KDA	70.00	71.60	70.80
	English	English	RF	71.10	74.70	72.90
Orientation and curvature features [8]	Arabic	Arabic	NN	71.00	65.00	68.00
	English	English	SVM	68.00	70.00	69.00
Proposed method using UGS	Arabic	Arabic	SVM	76.17	68.91	72.54
	English	English	SVM	80.31	73.06	76.68
Proposed method without UGS	Arabic	Arabic	SVM	74.61	69.95	72.28
	English	English	SVM	78.76	73.58	76.17

The evaluations in script-dependent mode perform better than those obtained with other scripts and exceed the script-independent experiments in terms of classification rates. Except for the experiment on Arabic samples of the QUWI dataset, the proposed approach outperforms other approaches in these experiments as well. In addition, in some cases, our proposed approach occasionally yields unsatisfactory classification results that are similarly homogeneous for male and female handwritings, and vice versa.

6. CONCLUSION

The goal of this research was to propose and evaluate the performance of different LBPs and their derivatives for generating feature vectors and classifying them using a SVM classifier. Results showed that they performed well in ICDAR 2013 contests that used script-dependent, script-independent, text-dependent, and text-independent evaluation modes. Performance on a subset of the QUWI dataset was examined, and the results showed that it performed well. The effectiveness of our method, which is based on the MLBPs methodology, was demonstrated through the results of experiments on a subset of the QUWI dataset in several evaluation modes. Our approach demonstrates its efficiency for script-dependent and script-independent offline handwritings when compared to the other approaches in the literature. In order to further increase the identification rates, we will continue to investigate this topic by looking at more features and the methodology for feature selection. Finally, we also intend to deduce other demographic characteristics from handwriting, including age and handedness.

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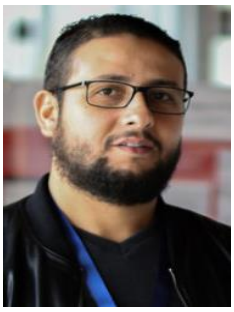

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