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Gender classification from offline multi-script handwriting images using oriented Basic Image Features (oBIFs)

Abdeljalil Gattal[a], Chawki Djeddi[a,*], Imran Siddiqi[b], Youcef Chibani[c]

[a] Department of Mathematics and Computer Science, Larbi Tebessi University, Tebessa, Algeria
[b] Department of Computer Science, Bahria University, Islamabad, Pakistan
[c] Communicating and Intelligent System Engineering Laboratory, Faculty of Electronic and Computer Sciences, University of Sciences and Technology Houari Boumédiene, Bab-Ezzouar, Algiers, Algeria

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ABSTRACT

Classification of gender from images of handwriting is an interesting research problem in computerized analysis of handwriting. The correlation between handwriting and gender of writer can be exploited to develop intelligent systems to facilitate forensic experts, document examiners, paleographers, psychologists and neurologists. We propose a handwriting based gender recognition system that exploits texture as the discriminative attribute between male and female handwriting. The textural information in handwriting is captured using combinations of different configurations of oriented Basic Image Features (oBIFs). oBIFs histograms and oBIFs columns histograms extracted from writing samples of male and female handwriting are used to train a Support Vector Machine classifier (SVM). The system is evaluated on three subsets of the QUWI database of Arabic and English writing samples using the experimental protocols of the ICDAR 2013, ICDAR 2015 and ICFHR 2016 gender classification competitions reporting classification rates of 71%, 76% and 68% respectively; outperforming the participating systems of these competitions. While textural measures like local binary patterns, histogram of oriented gradients and Gabor filters etc. have remained a popular choice for many expert systems targeting recognition problems, the present study demonstrates the effectiveness of relatively less investigated oBIFs as a robust textual descriptor.

1. Introduction

Computerized analysis of handwriting has been one of the most researched pattern classification problems (Plamondon & Srihari, 2000). In addition to the classical handwriting recognition problem, the fact that handwriting carries writer-specific information (Koppenhaver, 2007) makes its analysis an attractive area of research for forensic experts, document examiners, paleographers, psychologists and neurologists. The unique writing style of an individual makes handwriting an effective behavioral biometric modality with applications like writer identification, signature verification and personalized handwriting recognition systems. Handwriting being a complex fine motor skill (Caligiuri & Mohammed, 2012; Feder & Majnemer, 2007), is also known to be affected by a number of neurological disorders (Kushki, Chau, & Anagnostou, 2011; Schörter et al., 2003; Teulings & Stelmach, 1991), aging (Rosenblum, Engel-Yeger, & Fogel, 2013) and psychoactive medications (Caligiuri & Mohammed, 2012). Likewise, a number of psychological studies have shown the existence of correlation between handwriting and the personality traits of the writer (Klimoski & Rafaeli, 1983; Neter & Ben-Shakhar, 1989; Tett & Palmer, 1997). These personal attributes, however, are subjective and hard to validate scientifically. Consequently, neuroscientists and forensic experts distance themselves from graphologists and are more interested in neurological (rather than psychological) reasons of differences in handwritings of different individuals.

Unlike personal attributes, demographic attributes of writers are objective and can be validated through quantitative results. Both neuroscientists and psychologists agree on the existence of relationship between handwriting and different demographic attributes of writers including gender, handedness and age etc. Among these, gender of writer is known to be strongly correlated with the writing style (Beech & Mackintosh, 2005; Burr, 2002; Hamid & Loewenthal, 1996; Hartley, 1991; Hayes, 1996). Studies on prediction of gender through handwriting report that male handwritings are more 'spiky', 'hurried', 'untidy', 'scruffy' and 'sloping' . On the contrary, females handwritings tend to be more 'decorative', 'homogenous', 'delicate', 'regular', 'consistent', 'neat' and 'large' (Burr, 2002; Hartley, 1991). The differences in male and female handwriting are attributed by researchers to differences

* Corresponding author.
E-mail addresses: ab.gattal@univ-tebessa.dz (A. Gattal), c.djeddi@univ-tebessa.dz (C. Djeddi), imran.siddiqi@bahria.edu.pk (I. Siddiqi), ychibani@usthb.dz (Y. Chibani).

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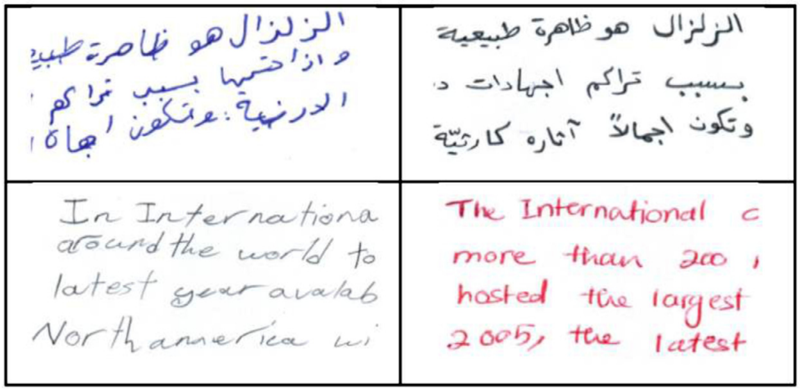

Fig. 1. Samples of male (on the left) and female (on the right) handwriting.

in motor control (Cohen, 1997; Dorfberger, Adi-Japha, & Karni, 2009; Hartley, 1991; Weintraub, Drory-Asayag, Dekel, Jokobovits, & Parush, 2007) and hormones (Hayes, 1996) between the two genders. Samples of Arabic and English writings supporting these observations are illustrated in Fig. 1.

Computerized systems for recognition of gender from handwriting are based image analysis and pattern classification techniques (Al-Maadeed & Hassaine, 2014; Liwicki, Schlapbach, & Bunke, 2011; Siddiqi, Djeddi, Raza, & Souici-meslati, 2012; Sokic, Salihbegovic, & Ahic-Djokic, 2012). Such systems, in general, algorithmically compute a subset of features employed by the human experts for analysis of handwriting (Goodenough, 1945; Hartley, 1991; Hayes, 1996). Although a two-class problem, gender classification is a challenging task as there is a large variation of handwriting styles within the same gender as well as considerable overlap between the two classes. Automatic gender classification systems strive to enhance the classification rates by improving the feature extraction or/and classification techniques, the two key components of any pattern recognition system. Combination of different features as well as multiple classifiers have also been investigated in the literature. The present study aims to enhance the feature extraction step for automatic classification of gender from handwriting images. We present an effective technique based on oriented Basic Image Features (oBIF) (Griffin & Lillholm, 2010; Griffin, Lillholm, Crosier, & Sande, 2009; Newell & Griffin, 2011; Newell & Griffin, 2013) to differentiate between male and female writings using Support Vector Machine (SVM) as classifier. The key contributions of this study include the following.

- Characterization of gender from handwriting exploiting oriented Basic Image Features.
- Script independent technique validated through a series of comprehensive multi-script experiments.
- Enhanced classification rates when compared to state-of-the-art techniques on this problem.

The proposed technique relies on binarizing the handwriting images and computing the oBIF extraction histogram (Gattal, Djeddi, Chibani, & Siddiqi, 2016; Newell, Griffin, Morgan, & Bull, 2010) and oBIF columns histogram (Gattal, Djeddi, Chibani, & Siddiqi, 2017; Newell & Griffin, 2011; Newell & Griffin, 2013). These are then concatenated together to form the feature vector. Writing samples of male and female writers are employed to train a one-against-all Support Vector Machine (SVM) that learns to discriminate between male and female writers. The proposed system is evaluated on Arabic and English writing samples of the well-known QUWI database in script-dependent as well as script-independent experiments. An overview of the proposed method is illustrated in Fig. 2.

The paper is organized as follows. Section 2 presents a discussion on well-known contributions to characterize gender from handwriting. Section 3 details the proposed methodology while Section 4 presents the experimental settings, realized results and a comparison with the state-of-the art techniques on this problem. Finally, the conclusions and a discussion on future research directions on the subject are presented in Section 5.

2. Related work

Correlation between handwriting and gender has been investigated in a number of studies. Among the pioneer studies, Goodenough (1945) presents a discussion on the discriminative attributes of male and female writings from the view point of psychologists. In Hartley (1991), conventional features characterizing gender based differences in handwritings are discussed while the impact of hormones on visual appearance of handwriting is presented in Hayes (1996). In another study (Hamid & Loewenthal, 1996), human analysts were provided with 30 writing samples (16 female and 14 male) as training set and were later required to categorize 25 documents (13 female and 12 male) into male and female handwriting. An average classification rate of 68% is reported in this work. It should be noted that being a two class problem, the chance performance is 50% hence all systems are expected to report a classification rate of more than 50%.

Computerized analysis of handwriting for classification of gender and other demographic attributes has gained significant attention of the handwriting recognition community in the recent years (Al-Maadeed & Hassaine, 2014; Bandi & Srihari, 2005; Liwicki et al., 2011; Siddiqi et al., 2012; Sokic et al., 2012), both for offline and online handwriting. Offline handwriting refers to the digitized images of handwritten samples acquired through scanning or by a camera. Online handwriting, on the other hand, is acquired on specialized digitizing tablets where in addition to the shape of characters, dynamic information of handwriting like speed, pressure, order and number of strokes etc. is also captured.

Among notable contributions, classification of three demographic attributes (race, age group and gender) using a set of macro and micro features is presented in Cha and Srihari (2001) with an average classification rate of around 70%. The same study was extended to carry out age, gender and handedness classification using a feed forward neural network with 800 writing samples in the training and 400 in the test set. Combination of multiple networks using bagging and boosting techniques was also investigated to enhance the system performance. Classification rates of as high as 77%, 86% and 74% are reported for gender, age and handedness respectively. In another recent work (Liwicki et al., 2011), classification of handedness and gender is in-

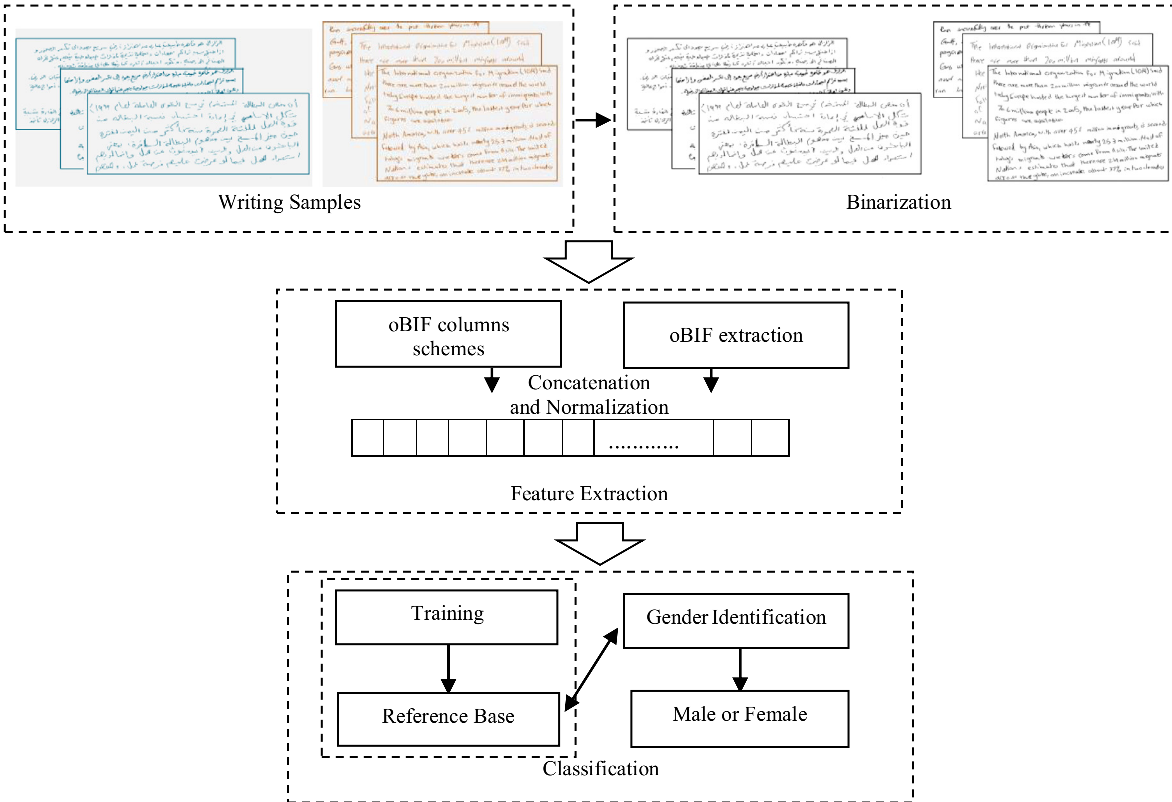

Fig. 2. Overview of the Proposed System.

vestigated using a combination of online and offline features. Evaluations on 200 writing samples (8 samples per writer) of the IAM-OnDB database report classification rates of 67% and 85% for gender and handedness respectively. Sokic et al. (2012) propose the use of features based on Fourier descriptors to characterize male and female handwritings. Likewise, Siddiqi et al. (2012) employ a combination of local and global features capturing the orientation, curvature and legibility information to discriminate male and female writings. Evaluations are carried out on QUWI and MSHD databases in a number of experimental scenarios using Support Vector Machine and Artificial Neural Network as classifiers.

Al-Maadeed and Hassaine (2014) studied the prediction of gender, age and nationality using random forests and kernel discriminant analysis with a set of geometrical features. The proposed scheme is validate through experiments in text-dependent and text-independent modes on samples of the QUWI database. The study was later extended (Al-Maadeed, Ferjani, Elloumi, & Jaoua, 2016) to investigate dimensionality reduction on handedness detection from offline handwriting. Textural features including Histogram of Oriented Gradients (HOG) and Local Binary Patterns (LBP) are applied with SVM classifier to predict gender from offline images of handwriting in Bouadjenek, Nemmour, and Chibani (2014). Experiments on 200 writing samples reported a maximum classification rate of 74%. The work was later extended (Bouadjenek, Nemmour, & Chibani, 2016) to other demographic attributes including age and handedness and was evaluated on QUWI and KHATT databases. SVM predictors based on pixel density, pixel distribution and Gradient Local Binary Patterns (GLBP), a variant of LBP, were combined using Fuzzy MIN-MAX combination (Bouadjenek, Nemmour, & Chibani, 2015) to carry out age, gender and handedness classification. In another study, Youssef, Ibrahim, and Abbott (2013), features based on gradient and Wavelet Domain Local Binary Patterns (WD-LBP) are employed to train a Support Vector Machine (SVM) to discriminate between male and female writings.

Among other recent studies on handwriting based gender classification, Mirza, Moetesum, Siddiqi, and Djeddi (2016) exploit texture based features to characterize gender from handwriting. A bank of Gabor filters is applied to handwriting image and the mean and standard deviation values of the filter responses are collected in a matrix. The Fourier transform of the matrix is employed as feature to train a feed forward neural network. Evaluations on the QUWI database under different experimental settings report a highest classification rate of 70%. In another recent work, Akbari, Nouri, Sadri, Djeddi, and Siddiqi (2017) investigate the application of wavelet sub-bands to handwriting images to predict gender from handwriting. While most of the studies on gender classification aim to enhance the feature extraction step, Ahmed, Rasool, Afzal, and Siddiqi (2017) investigated the performance of multiple classifiers and their combinations using traditional textural features. Experiments on different subsets of the QUWI database reported classification rates ranging from 79% to 85%. Authors demonstrated that combining multiple classifiers through techniques like stacking, bagging and boosting enhances the classification rates. The enhancement, however, was not very significant once compared to individual classifiers.

Like many other recognition problems, a relatively recent trend in handwriting based writer and writer demographics classification is the application of deep convolutional neural networks (CNNs) to automatically extract effective feature representations from the handwriting images (Morera, Sánchez, Vélez, & Moreno, 2018; Xing & Qiao, 2016; Yang, Jin, & Liu, 2016). The major challenge in such techniques is the requirement of considerable amount of training data. Since the current handwriting databases have the magnitude of few thousands, data augmentation techniques are generally applied to generate sufficient training data for the deep networks. Furthermore, these CNN based techniques

Table 1
An overview of notable gender classification techniques.

Study	Features	Classifier	Dataset	Classification Rate
Cha and Srihari (2001)	A set of macro and micro features	ANN	CEDAR	70.20%
Liwicki et al. (2011)	Combination of online & offline features	GMM	IAM-OnDB	67.57%
Sokic et al. (2012)	Shape Descriptors	–	BHDH	–
Siddiqi et al. (2012)	Orientation, curvature & legibility features	SVM	QUWI & MSHD	68.75% / 73.02%
Al-Maadeed and Hassaine (2014)	Geometrical Features	Random Forests	QUWI	73%
Bouadjenek et al. (2014)	HOG & LBP features	SVM	IAM	74%
Youssef et al. (2013)	Gradient & WD-LBP features	SVM	QUWI	74.30%
Mirza et al. (2016)	Gabor filters & Fourier transform	ANN	QUWI	70%
Akbari et al. (2017)	Wavelet sub-bands	SVM/ANN	QUWI & MSHD	80%
Ahmed et al. (2017)	Textural Features	Ensemble of classifiers	QUWI	79 - 85%

require fixed-size input images; word and line level images have been the two popular choices. Among notable studies, Xing and Qiao (2016) present a deep CNN architecture for text-independent writer identification. The architecture is inspired from the AlexNet structure (Krizhevsky, Sutskever, & Hinton, 2012) and reports high identification rates on English as well as Chinese writing samples. In another similar work, Yang et al. (2016), introduce a new data augmentation technique to enhance the generalization capability of CNNs and demonstrate the effectiveness of the proposed technique through online writer identification.

For demographic classification, Morera et al. (2018) proposed a deep CNN architecture for prediction of gender and handedness from handwriting images. The proposed architecture comprises six trainable layers and receives 30×100 images as input. Affine transformations and morphological operators are applied as data augmentation techniques. Experiments report gender classification rates of 81% and 69% on writing samples of IAM and KHATT databases respectively. Likewise, handedness classification rates read 91% on IAM and 71% on KHATT database. An interesting aspect of this research is the use of same network configuration for both English and Arabic writing samples for gender as well as handedness classification.

Three competitions on gender detection using the QUWI database have been held in conjunction with ICDAR 2013 (Hassaine, Al-Maadeed, Aljaam, & Jaoua, 2013), ICDAR 2015 (Djeddi et al., 2015) and ICFHR 2016 (Djeddi et al., 2016). A major proportion of the gender classification methods discussed above report their results on a subset of the QUWI database using experimental protocols of one (or more) of these competitions. The system ranked first (CVC method) in the ICDAR 2015 competition (Djeddi et al., 2015) employed local binary patterns while the winning system of the ICFHR 2016 competition (Djeddi et al., 2016) used a combination of textural descriptors (local binary patterns, histogram of oriented gradients and gray level co-occurrence matrices) to characterize gender from handwriting. A detailed comparison and analysis of results of these competitions and those realized by the proposed technique is presented in Section 4.

A summarized review of different handwriting based gender classification techniques is presented in Table 1. It can be seen that in most cases, features employed for problems like writer identification and verification have been adapted for gender classification (Cha & Srihari, 2001; Liwicki et al., 2011; Siddiqi et al., 2012). Texture has been the most widely employed discriminative attribute (Bouadjenek et al., 2014; Mirza et al., 2016; Youssef et al., 2013) and the textural information in handwriting has been captured through features like local binary patterns (LBP), histogram of oriented gradients (HoG) and Gabor filters etc. QUWI database has been a popular choice for experimental evaluation of the developed systems and different subsets of this database have been employed in different studies. In general, the classification rates of different studies vary between 70% - 80% for different experimental scenarios. Few of the recent studies investigate the effectiveness of high level descriptors like Scale Invariant Feature Transform (SIFT) (Wu, Tang, & Bu, 2014; Xiong, Wen, Wang, & Lu, 2015) and bag of visual words models (Fiel & Sablatnig, 2013; Gordo, Fornés, & Valveny, 2013) for identification of writers from handwriting and it would be interesting to study the performance of such features on the more general gender classification problem. With a few exceptions, the contribution of different studies on this problem lies in the feature extraction step while classification is carried out using the traditional classifiers (ANN or SVM in most cases).

After having discussed the significant recent contributions to classification of gender from handwriting, we present the proposed methodology in the next section.

3. oBIF Based Gender Classification

The proposed gender classification technique relies on two main components, feature extraction and classification (Fig. 2). The handwriting image is first binarized using global thresholding and features based on oBIFs histogram and oBIFs columns histogram are extracted. These features are then employed to train an SVM classifier. Each of these modules is discussed in detail in the following.

3.1. Feature extraction

We aim to exploit the textural differences between male and female writings to discriminate between the two classes. Textural measures like Histogram of Oriented Gradients (HOG), Local Binary Patterns (LBP) and their variants and Gabor filters have been previously applied to gender detection problem in a number of studies (Bouadjenek et al., 2014; Bouadjenek et al., 2015; Mirza et al., 2016; Youssef et al., 2013). The present study investigates the effectiveness of oBIFs in characterizing gender from handwriting. oBIFs have been applied to problems like character recognition (Newell & Griffin, 2011), writer identification (Newell & Griffin, 2013) and handwritten digit recognition (Gattal et al., 2016) and have reported high classification rates. More specifically, we extract oBIFs histogram and oBIFs columns histogram and concatenate the two to obtain the final feature vector. Each of these is discussed in the following.

3.1.1. oBIFs histogram

The oriented Basic Image Features (oBIFs) represent a texture-based descriptor which is an extension to the Basic Image Features (BIFs) (Griffin & Lillholm, 2010; Griffin et al., 2009). Every location in the image is categorized into one of the seven local symmetry classes according to local symmetry type, which can be flat, slope, dark rotational, light rotational, dark line on light, light line on dark or saddle-like (Fig. 3). The classification is based on the response of a bank of six Derivative-of-Gaussian filters (up to second order) of size determined by the scale parameter σ. The parameter ε is used for classifying the likelihood of location as flat. The

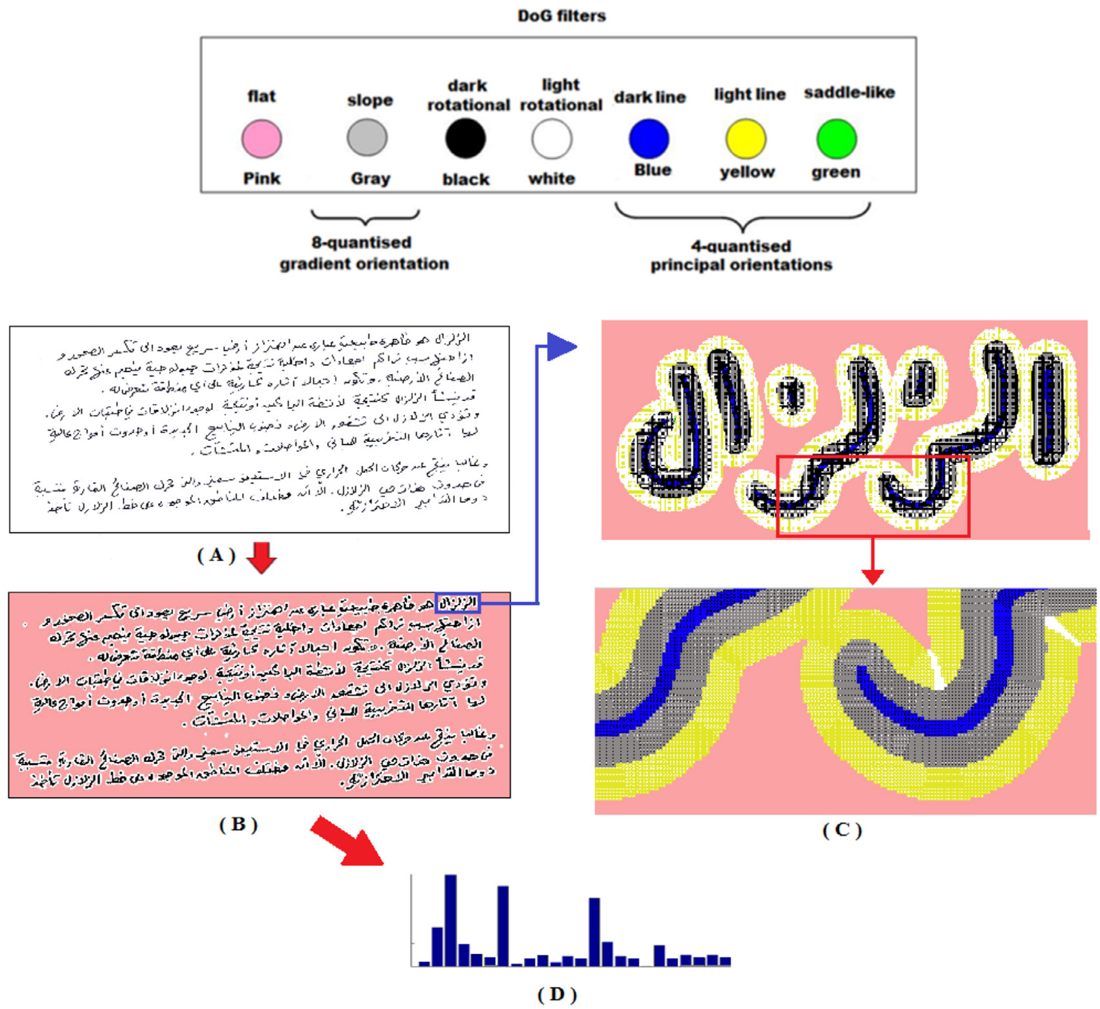

Fig. 3. Steps in extraction of oBIFs histogram for handwritten document with $\sigma = 4$ and $\varepsilon = 0.001$. (A) Binarized handwritten document image (B) oBIFs image (C) Example of texture information from oBIFs (D) Histogram of oBIFs.

local orientation that can be assigned to each location in the image depends on the local symmetry type as follow.

- For the dark line on light, light line on dark and saddle-like classes, n possible orientations can be assigned.
- For the slope class, $2n$ possible orientations can be assigned.
- The dark rotational, light rotational and flat types have no orientation.

The dimension of the oBIF feature vector, therefore, is $5n+3$. In our study, the orientations are quantized into $n=4$ levels thus producing 23 entries in the oBIFs dictionary. For handwriting images under consideration, we employ the 23 bin oBIFs histogram as feature. As a function of the local symmetry type and orientation, each pixel in the writing image is assigned to the respective bin in the histogram which is finally normalized. Fig. 3 illustrates a sample handwritten document encoded using the oBIFs and the corresponding histogram.

3.1.2. The oBIFs column histogram scheme

In order to increase the performance of the oBIFs descriptor, we combine oBIFs at two different scales to produce the oBIF column features (Newell & Griffin, 2011; Newell & Griffin, 2013) by ignoring the symmetry type flat. This increases the dimension of the oBIF column histogram to $(5n+2)^2$, i.e. 484 in our case. The oBIF column features are generated using different values of the scale parameter $\sigma \in \{1, 2, 4, 8, 16\}$ while the parameter ε is fixed to one of the three small values $\varepsilon \in \{0.1, 0.01, 0.001\}$. The generated feature vector is finally normalized. Different steps of the oBIFs column scheme are summarized in Fig. 4.

Once the oBIFs and oBIFs column histograms are extracted, they are concatenated together to form the feature vector representing each handwriting image. The final vector is standardized to have zero mean and unit variance. By varying the parameters σ and ε different configurations of oBIFs histograms and oBIFs column histograms are generated. These configurations are discussed in detail in Section 4.

3.2. Classification

Once the features are extracted, classification is carried out using Support Vector Machine (SVM) classifier (Hsu & Lin, 2002; Vapnik, 1995). oBIFs histograms and oBIFs column histograms extracted from male and female writings are used to train the SVM to make it learn the two classes. We have employed the Radial Basis Function (RBF) kernel with the kernel parameter selected in the range [0, 100] while the soft margin parameter C is fixed to 10.

4. System evaluation

The effectiveness of the proposed technique is validated by a series of experiments. We first endeavor to find the optimal configuration of oBIFs (and their concatenation) by using mixed (both

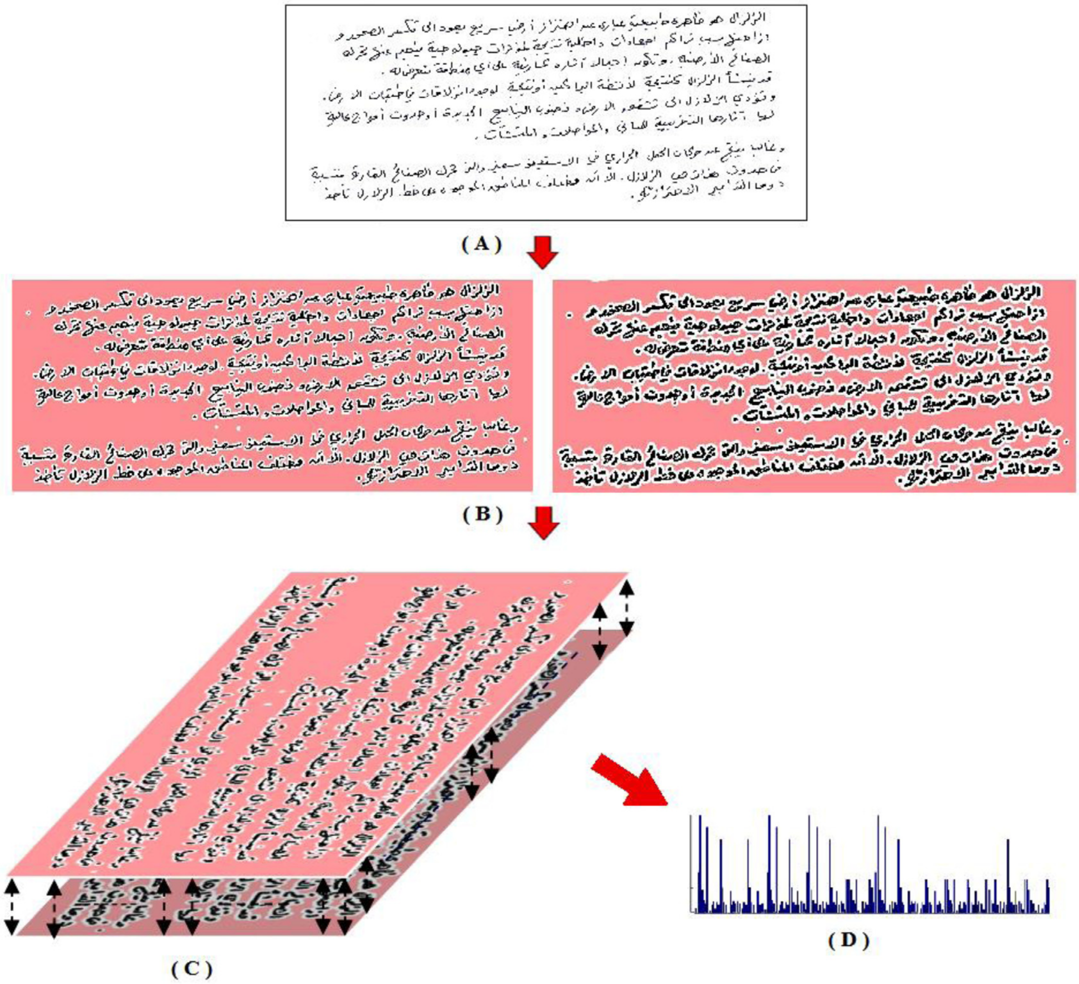

Fig. 4. Different steps of the oBIF Column scheme (A) Original image (B) oBIFs computation for scale parameter $\sigma = 4$ and $\sigma = 8$ while $\varepsilon = 0.001$ (C) The oBIFs at two scales are crossed to form columns at each location (D) the histogram is computed with non-flat columns.

Arabic and English) samples of the QUWI database in training and test sets. The best configurations of features identified by these experiments are then employed to carry out script-dependent and script-independent evaluations. In order to allow a meaningful comparison, the experiments are carried out on a subset of the QUWI database using the same experimental protocols as those of the ICDAR 2013, ICDAR 2015 and ICFHR 2016 competitions. We first present the details of the QUWI database and the experimental settings of the three competitions followed by a discussion on the realized results.

4.1. Database and experimental protocol

As mentioned earlier, all experiments are carried out on different subsets of the Qatar University Writer Identification (QUWI) database (Al-Maadeed, Ayouby, Hassaine, & Aljaam, 2012). Although the database has been primarily developed for evaluation of writer identification systems, the gender information of each contributor has also been stored allowing the database to be employed for gender classification systems as well. Each writer in the database provided 4 samples, 2 in Arabic and 2 in English. Page 1 and Page 3 of each writer comprise an arbitrary text in Arabic and English respectively while Page 2 and Page 4 contain a fixed text for each writer. The database has been employed in three International competitions on handwriting based gender classification. The details of the respective experimental protocols are presented in the following.

4.1.1. ICDAR2013 competition protocol

The database employed in the ICDAR 2013 competition (Hassaine et al., 2013) comprised 475 writers from the QUWI database. The training set consisted of 282 writers (564 writing samples in English and Arabic each) while 193 writers constituted the test set with 386 samples in Arabic and 386 in English.

4.1.2. ICDAR 2015 competition protocol

The ICDAR2015 competition (Djeddi et al., 2015) comprised four different tasks and each task was based on 500 handwritten samples, with 300 in the training set, 100 in the validation set and 100 in the test set. The most interesting aspect of the competition was that the challenges involved both script-dependent (Tasks 2A and 2B) as well as script- independent (Tasks 2C and 2D) experiments.

4.1.3. ICFHR 2016 competition protocol

The ICFHR 2016 (Djeddi et al., 2016) competition was based on the same four tasks as those of the ICDAR 2015 competition with the number of samples per task increased to 1000. 500 samples were provided as training set, 250 as validation and 250 as test set.

Table 2 summarizes the distribution of samples and writers in the three competitions.

Table 2
Distribution of writers and samples in the three gender classification competitions.

Competition:	ICDAR 2013	ICDAR 2015	ICFHR 2016
Total writers	475	500	1000
Training set	282	300	500
Validation set	–	100	250
Test set	193	100	250
Gender	Male: 221	Male: 250	Male: 487/500
	Female: 254	Female: 250	Female: 513/500
Samples/writer	4 (2 Arabic,2 English)	4 (2 Arabic,2 English)	3(1 Arabic, 2 English)

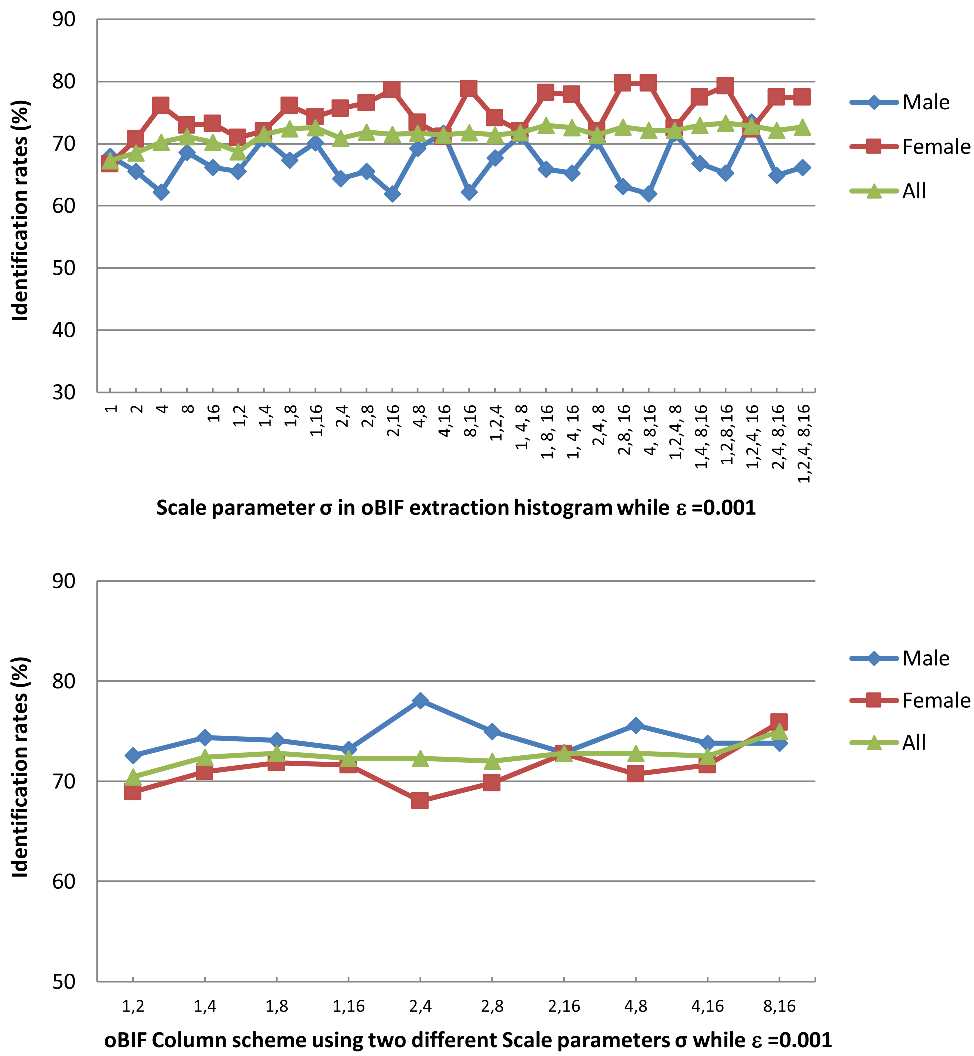

Fig. 5. Classification rates on QUWI database - ICDAR 2013 Experimental settings.

All evaluations are carried out using the experimental protocols of the three competitions. Classification rates are studied as a function of the parameters σ and ε in the oBIFs histograms and oBIFs column histograms. Features extracted using different configurations of these parameters are concatenated to enhance the classification rates. The realized results are also compared with a number of well-known existing techniques. The following sections present the details of these experiments.

4.2. Evaluations on mixed samples

These experiments are carried out by using both Arabic and English samples of male and female writers in the training and test sets. For the ICDAR 2013 dataset, the 564 Arabic and 564 English samples of 282 writers are combined together to constitute the training set. Likewise, the test set is produced by combining the 386 Arabic and 386 English samples of the 193 test writers. In a similar fashion, for the ICDAR 2015 database, the training set comprises 600 writing samples (300 in Arabic and 300 in English) while the test set consists of 200 query samples (100 each in Arabic and English). For the ICFHR 2016 competition database, we generate a training set of 1000 samples and a test set of 500 samples in Arabic and English. These experiments aim to study the effect of the scale parameter σ and the parameter ε in computing the oBIFs histogram and the oBIFs column histogram. The realized classification rates are illustrated in Figs. 5–7 corresponding to the databases of the ICDAR 2013, ICDAR 2015 and ICFHR 2016 competitions respectively.

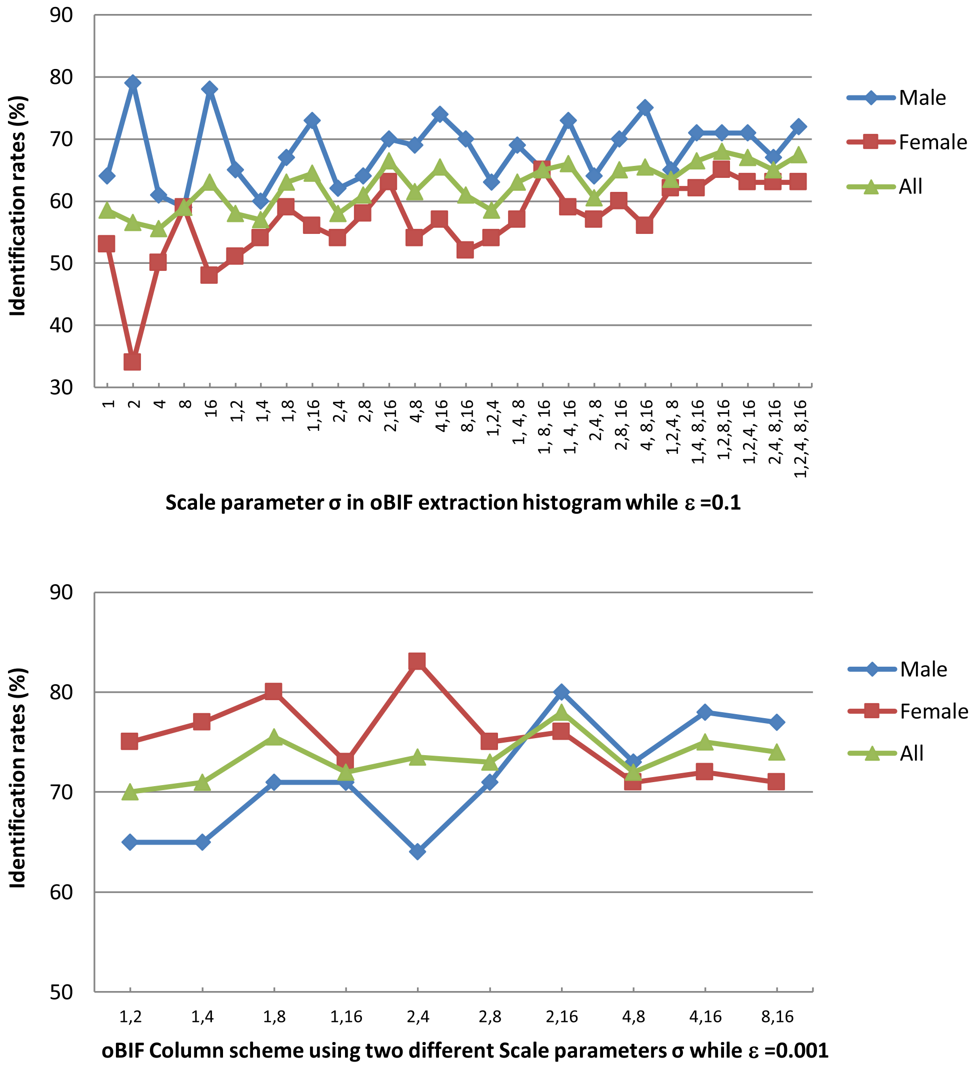

Fig. 6. Classification rates on QUWI database - ICDAR 2015 Experimental settings.

It can be seen from Figs. 5–7 that the oBIFs column histograms outperform the oBIFs histograms in all scenarios. This is due to the combination of best oBIFs at two scales. A summary of the best performing configurations of oBIFs features and their various combinations is presented in Table 3. It can be seen that by combining the different configurations of oBIFs histograms and oBIFs columns histograms, classification rates of as high as 76.17%,78.50% and 75.60% are realized on three subsets of the QUWI database using the experimental settings of the three competitions.

4.3. Script-dependent evaluations

Script dependent evaluations are carried out by having the same script (English or Arabic) in the training and test sets. These experiments correspond to tasks 2A and 2B in the ICDAR 2015 and ICFHR 2016 competitions. We compare the performance of the proposed features with those of the best performing systems in the three competitions as well as other studies in the literature which have employed the experimental protocols of these competitions. With a couple of exceptions, all reported studies employ SVM classifier and focus more on the feature extraction step. The comparison is summarized in Table 4 where it can be observed that the oBIFs outperform other techniques in all three experimental settings realizing average classification rates of 77.07%, 79.50% and 75.00%. Another interesting observation is that in many studies, inconsistencies can be seen in the classification rates on Arabic and English writing samples. This may be attributed to the fact the extracted features in these studies could be more effective on a particular script. The proposed technique reports more or less similar classification rates on both Arabic and English samples demonstrating that the oBIFs characterize gender from handwriting equally good in different scripts.

Another interesting comparison is among the classification rates of our own technique across the three experimental settings. While the number of writers in ICDAR 2013 settings is lesser than those in the ICDAR 2015 protocol, a relatively lesser classification rate of 77.07% is observed as compared to that of 79.50%. This observation can be attributed to the fact that the training to test samples ratio is 1.5:1 in the ICDAR 2013 database while it is 3:1 in the samples of ICDAR 2015 competition. A classification rate of 75% is reported on the ICFHR 2016 database where the test set comprises 250 writers with a training to test ratio of 2:1.

4.4. Script-Independent evaluations

The script independent evaluations represent a more challenging scenario where the training and test samples belong to different scripts. These experiments aim to validate the hypothesis that gender can be characterized from handwriting irrespective of the script under study. Individuals belonging to a gender group (male

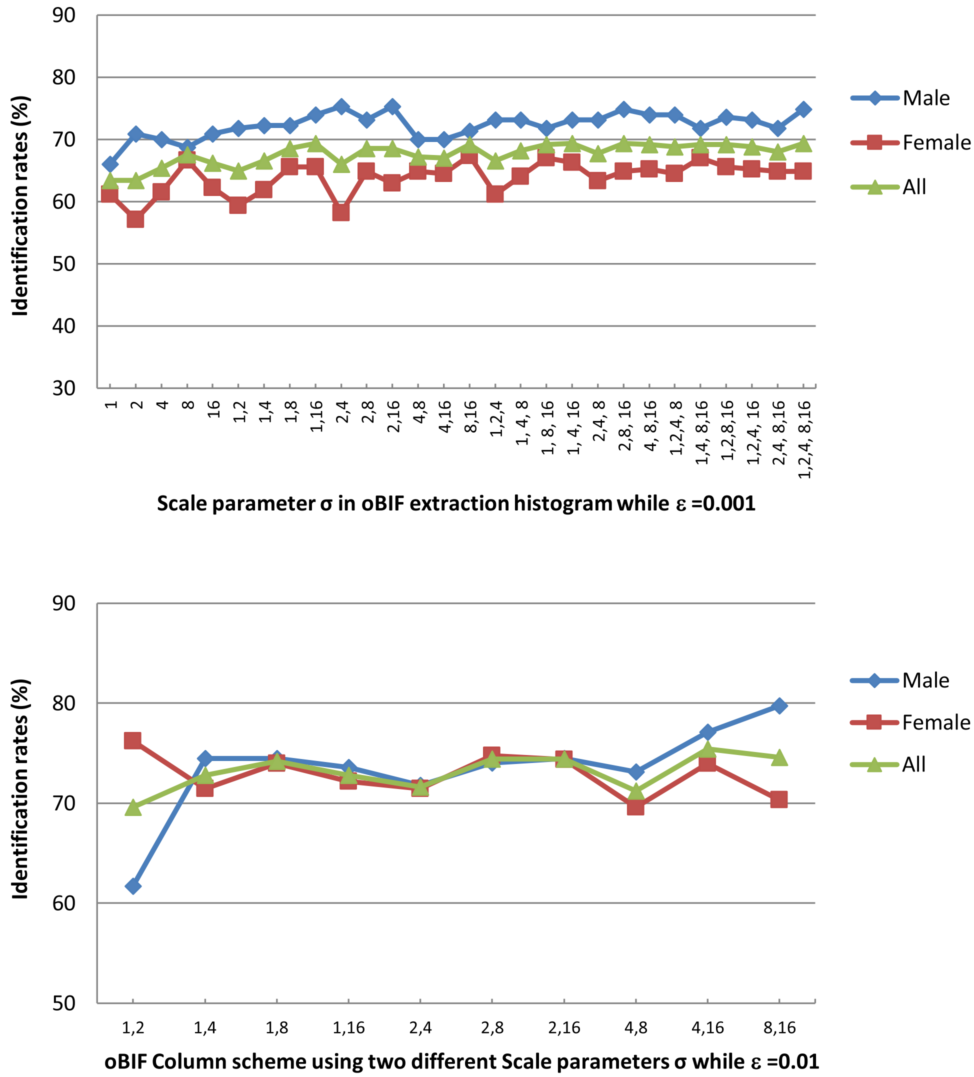

Fig. 7. Classification rates on QUWI database - ICFHR 2016 Experimental settings.

Table 3
Gender classification rates on mixed samples of the QUWI database with different configurations of oBIFs using the datasets of the three competitions.

Competition	Features		oBIF Parameters	Dim.	Classification rate		
					Male	Female	All
ICDAR 2013	*f1*	oBIF columns histogram	oBIFs at $\sigma = 8$ & $\varepsilon = 0.001$ oBIFs at $\sigma = 16$ & $\varepsilon = 0.001$	484	73.78	75.90	75.00
	f2	oBIF columns histogram	oBIFs at $\sigma = 4$ & $\varepsilon = 0.1$ oBIFs at $\sigma = 8$ & $\varepsilon = 0.1$	484	78.96	68.69	73.06
	f3	oBIF extraction histogram	oBIFs at $\sigma = \{1, 2, 4\}$ & $\varepsilon = 0.1$	69	77.74	63.74	69.69
	f4	oBIF histogram	oBIFs at $\sigma = \{1, 2, 8, 16\}$ & $\varepsilon = 0.001$	92	65.24	79.28	73.32
	f1,f2			968	77.13	73.87	75.26
	f1, f2, f3, f4			**1129**	**78.05**	**74.77**	**76.17**
ICDAR 2015	*f1*	oBIF columns histogram	oBIFs at $\sigma = 2$ & $\varepsilon = 0.001$ oBIFs at $\sigma = 16$ & $\varepsilon = 0.001$	484	76.00	80.00	78.00
	f2	oBIF extraction histogram	oBIFs at $\sigma = \{2\}$ & $\varepsilon = 0.1$	23	79.00	34.00	56.50
	f1, f2			**507**	**75.00**	**82.00**	**78.50**
ICFHR 2016	*f1*	oBIF columns histogram	oBIFs at $\sigma = 4$ & $\varepsilon = 0.01$ oBIFs at $\sigma = 16$ & $\varepsilon = 0.01$	484	77.09	73.99	75.40
	f2	oBIF columns histogram	oBIFs at $\sigma = 8$ & $\varepsilon = 0.01$ oBIFs at $\sigma = 16$ & $\varepsilon = 0.01$	484	79.74	70.33	74.60
	f3	oBIF histogram	oBIFs at $\sigma = \{8, 16\}$ & $\varepsilon = 0.001$	46	71.37	67.40	69.20
	f1,f2,f3			1014	78.41	68.50	73.00
	f1,f2			**968**	**77.97**	**73.63**	**75.60**

Table 4
Comparison of classification rates in script-dependent evaluations.

Competition	Method	Script		Classifier	Classification rate	
		Train	Test		Script-dependent	Average
ICDAR 2013	Proposed method	Arabic	Arabic	SVM	**76.17**	**77.07**
		English	English		**77.98**	
	Akbari et al. (2017)	Arabic	Arabic	SVM	77.70	76.60
		English	English		75.50	
	Siddiqi et al. (2012)	Arabic	Arabic	SVM	68.50	68.50
		English	English		68.50	
	Youssef et al. (2013)	Arabic	Arabic	SVM	68.60	77.15
		English	English		85.70	
	ICDAR features (Hassaine et al., 2013)	Arabic	Arabic	SVM	62.30	69.70
		English	English		77.10	
ICDAR 2015	Proposed method	Arabic	Arabic	SVM	**78.00**	**79.50**
		English	English		**81.00**	
	Mirza et al. (2016)	Arabic	Arabic	NN	70.00	68.50
		English	English		67.00	
	CVC method (Djeddi et al., 2015)	Arabic	Arabic	–	65.00	61.00
		English	English		57.00	
	Nuremberg method (Djeddi et al., 2015)	Arabic	Arabic	SVM	62.00	61.00
		English	English		60.00	
ICFHR 2016	Proposed method	Arabic	Arabic	SVM	**74.80**	**75.00**
		English	English		**75.20**	
	MCS-NUST Method-1 (Djeddi et al., 2016)	Arabic	Arabic	SVM	61.60	58.80
		English	English		56.00	
	MCS-NUST Method-2 (Djeddi et al., 2016)	Arabic	Arabic	SVM + Bagging	60.80	59.20
		English	English		57.60	
	Nuremberg Method-1 (Djeddi et al., 2016)	Arabic	Arabic	SVM	58.00	56.00
		English	English		54.00	
	Nuremberg Method-2 (Djeddi et al., 2016)	Arabic	Arabic	SVM	46.40	60.20
		English	English		74.00	

or female) share common attributes which are persistent across multiple scripts and oBIFs are an effective representation to capture these attributes. The experiments are carried out by first using the Arabic samples in the training set and English samples in the test set. The scenario is then reversed by using the English samples as the training set and the Arabic writings as the test set. These experiments correspond to Tasks 2C and 2D in the ICDAR 2015 and ICFHR 2016 competitions. These experiments were not a part of the ICDAR 2013 competition. However, few recent studies have reported the results of script-independent evaluations on the ICDAR 2013 database and make a part of our comparative study. Table 5 summarizes the classification rates of different studies in script-independent mode using the experimental setup of the three competitions.

Similar to the script-dependent experiments, the proposed method outperforms other techniques in the script-independent evaluations as well achieving classification rates of 71.37%, 76.00% and 68.00% for the ICDAR 2013, ICDAR 2015 and ICFHR 2016 experimental settings respectively. The trend is similar to the one observed in script-dependent evaluations (Table 4) where the highest classification rate is realized on the ICDAR 2015 database. In general, the classification rates of script-independent evaluations are relatively low as compared to those of the script-dependent evaluations. This observation is consistent not only for our proposed technique but for all the studies reported in Tables 4 and 5. As discussed earlier, script-independent evaluations are more challenging as the training and test sets comprise writing samples in different scripts. Considering the difficulty of the problem, classification rates of 71.37%, 76.00% and 68.00% are indeed very promising. Although a two class problem, in some cases, male and female writings tend to be visually very similar (Fig. 8) making classification of gender a very challenging task.

In an attempt to provide an insight into how the oBIFs characterize male and female handwriting, we illustrate (highly) gendered handwriting samples in Fig. 9 with the application and visualization of the features. The female samples are relatively homogenous and neat while the male handwriting seems to be spiky and hurried. It can be observed that for both the scripts, the distribution of symmetry types is more or less similar in writing samples produced by writers of the same gender. Other studies exploiting texture as the discriminative attribute between male and female handwriting (Mirza et al., 2016; Siddiqi et al., 2012) also employ the same hypothesis, i.e. attributes like neatness and homogeneity can be effectively used to characterize gender from handwriting.

From the view point of theoretical comparison with other techniques, we share the idea of considering handwriting as a texture and exploiting the textural information to characterize the gender of writer. Unlike the commonly employed textural measures like LBP (and its variants), HOG or Gabor filters, we investigated different configuration of oBIFs and their various combinations. These features proved to be more effective textural descriptors in capturing the correlation between handwriting and gender. The performance is also not very sensitive to different parameters involved in the computation of these features as validated through experiments. The features, however, are computationally expensive and the dimensionality of the feature vector can be large (for some configurations). It would be interesting to study which local orientations in the descriptor contribute more to predict the gender of writer. Feature selection techniques or extraction of weighted histograms can be investigated in this regard to come up with a more robust descriptor.

5. Conclusion

An effective technique for characterizing gender from handwriting is presented that exploits oBIFs and employs the oBIFs histograms and oBIFs columns histograms as features. Different configurations of oBIFs are investigated with SVM classifier. A comprehensive series of experiments is carried out using writing sam-

Table 5
Comparison of classification rates in script-independent evaluations.

Competition	Method	Script		Classifier	Classification rate	
		Train	Test		Script-Independent	Average
ICDAR 2013	Proposed method	Arabic	English	SVM	**73.32**	**71.37**
		English	Arabic		**69.43**	
	Akbari et al. (2017)	Arabic	English	SVM	69.40	69.00
		English	Arabic		68.60	
	Siddiqi et al. (2012)	Arabic	English	ANN	65.00	65.00
		English	Arabic		65.00	
ICDAR 2015	Proposed method	Arabic	English	SVM	**76.00**	**76.00**
		English	Arabic		**76.00**	
	Mirza et al. (2016)	Arabic	English	ANN	69.00	66.00
		English	Arabic		63.00	
	CVC method (Djeddi et al., 2015)	Arabic	English	–	63.00	60.50
		English	Arabic		58.00	
	Nuremberg method (Djeddi et al., 2015)	Arabic	English	SVM	55.00	54.00
		English	Arabic		53.00	
ICFHR 2016	Proposed method	Arabic	English	SVM	**66.00**	**68.00**
		English	Arabic		**70.00**	
	MCS-NUST method-1 (Djeddi et al., 2016)	Arabic	English	SVM	57.60	58.60
		English	Arabic		59.60	
	MCS-NUST2 method-2 (Djeddi et al., 2016)	Arabic	English	SVM + Bagging	58.40	58.80
		English	Arabic		59.20	
	Nuremberg method-1 (Djeddi et al., 2016)	Arabic	English	SVM	56.00	58.60
		English	Arabic		61.20	
	Nuremberg method-2 (Djeddi et al., 2016)	Arabic	English	SVM	72.40	58.80
		English	Arabic		45.20	

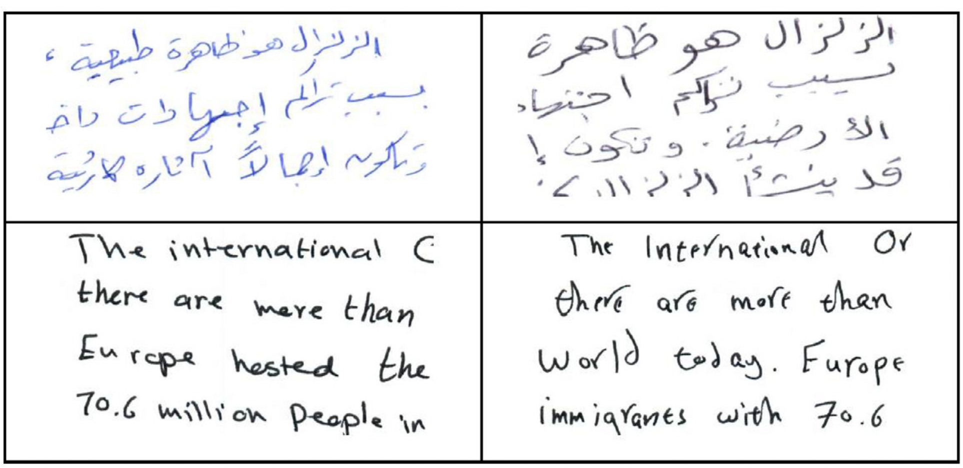

Fig. 8. Visually similar male (on the left) and female (on the right) writings.

Fig. 9. Writing samples of male (on the left) and female (on the right) writers with application of oBIFs.

ples in the QUWI database. Evaluations are carried out using the experimental settings of three International competitions on this problem and the results are compared with state-of-the-art existing techniques reported in the literature. The proposed technique outperforms the existing methods in script-dependent as well as script- independent modes.

In our further study on this problem, we intend to investigate the effectiveness of oBIFs in characterizing other demographic attributes of writers including age and handedness. Study of other textural measures to characterize gender from handwriting and exploration of feature selection techniques to identify the most appropriate textural descriptors for this problem is also planned. It is interesting to note that for a problem like gender classification, a subset of the attributes identified by the document examiners are algorithmically computed to develop automated systems. In case of gender, the differences between male and female handwritings can be intuitively explained. This, however, is not the case with other demographic attributes like age, handedness or education level etc. In most cases, computerized studies predicting these attributes from handwriting compute a set of statistical features from writing samples while the classifier learns the mapping between input (features) and output (demographic attributes) variables without any intuitive explanation. More investigations are required by document examiners as well as by computer scientists to identify the writing properties which are correlated with the demographic attributes of writers. Another interesting but relatively less explored area is the development of intelligent systems to predict neurological and psychological disorders from handwriting and hand-drawn shapes. The major challenge in developing such systems is the availability of databases with writing samples of control subjects and subjects with neurological problems. Likewise, many of the psychological studies tend to be subjective (personality profiling for instance) and quantitative evaluation of expert systems targeting these problems is often debated by the computer scientists. From the broader view point of computerized analysis of handwriting, an interesting direction is the use of hyper-spectral imaging techniques to capture handwriting images. The rich information in multiple bands of hyper-spectral handwriting images can be exploited to develop robust applications like signature verification and forensic examination.

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