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Gender Classification from Offline Handwriting Images using Textural Features

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***Abstract*—Prediction of gender and other demographic attributes of individuals from handwriting samples offers an interesting basic, as well as applied research problem. The correlation between gender and the visual appearance of handwriting has been validated by a number of studies and the present study is based on the same idea. We exploit the textural measurements as the discriminating attribute between male and female writings. The textural information in a writing is captured by applying a bank of Gabor filters to the image of handwriting. The mean and standard deviation values of the filter responses are collected in matrix and the Fourier transform of the matrix is used as a feature. Classification is carried out using a feed forward neural network. The proposed technique evaluated on a subset of the QUWI database realized promising results under different experimental settings.**

***Keywords*—Handwriting; Gender Classification; Textural Features; QUWI Database;**

I. Introduction

Handwriting is an established biometric modality that has been employed by document examiners, psychologists, forensic analysts, graphologists and palaeographers for many decades now [1], [2], [3], [4]. Research [5], [6], [7], [8] has shown that handwriting contains rich information about the writer which not only allows identifying the authorship of a handwritten document but also enables personality profiling through analysis of handwriting [3], [4]. Likewise, identification of a number of demographic traits such as handedness, age and gender from handwriting has also been explored in a number of studies [1], [2]. While the existence of a meaningful relationship between personality traits and handwriting remains debatable [5], [6], [7], [8], a valid correlation is known to exist between handwriting and the gender of an individual [9], [10], [11], [12], [13], [14], [15], [16], [17].

Among the earliest works on (manual) classification of gender from handwriting, Goodenough [11] discusses the differences between writings of male and female writers. Likewise, Hartely [13] summarized a set of features that could be exploited to differentiate between male and female writings while Hayes [14] discussed the correlation between hormones and writing style. Hamid et al. [12] collected a database of 30 handwritings in English and Urdu and carried out experiments where human experts classified the samples into two classes, male and female writers. An average classification rate of 68% is reported in the study.

The key differences identified by psychologists and document examiners between male and female writings are based primarily on the visual appearance of the writing. Male writings tend to be 'spiky' and 'hurried' while female writings, in general, are more 'decorative' and 'homogenous' [10], [13]. With the advancements in computerized analysis of handwriting, automatic systems have been developed to algorithmically compute a subset of the features which serve to discriminate male and female writings.

Among automated analysis of handwriting, a system for demographic classification of individuals is presented in [2] where the authors predict age group, gender and handedness of the writer with an average classification rate of around 70%. Liwicki et al. [18] extracted a set of online and offline features to predict gender and handedness from online handwriting samples. Classification is carried out using Support Vector Machine (SVM) and Gaussian Mixture Models (GMM) and classification rates of 67% and 85% are realized for gender and handedness prediction respectively on a database of 200 writers. In another study [19], authors propose the combination of Fourier descriptors with tangent and curvature information and bending energy, to classify gender from handwritten samples. Likewise, Siddiqi et al. [20] compute a set of global and local features capturing information on the curvature, slant, texture and legibility of writing. These features are used to train two classifiers, Support Vector Machine and Artificial Neural Network. Results of the study are reported on QUWI and MSHD databases reading classification rates from 68% to 74% .

In another recent study [21], geometric features are exploited to characterize the gender, age group and handedness of writers. For classification, the authors employ random forests and kernel discriminant analysis. Evaluations are carried out the writing samples in the QUWI database in text-independent as well as text-dependent mode and classification rates of up to 74% are reported. In another study by the same authors [22], a dimensionality reduction scheme is proposed and is evaluated on handedness detection from handwriting. The authors conclude that more than 30% reduction in dimensionality of feature vector is realized while maintaining high classification rates. Bouadjenek et al. [23] employed the Histogram of Oriented Gradients (HOG) and

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Local Binary Patterns (LBP) with SVM classifier to detect gender from handwriting. Evaluations on 200 writers of the IAM-onDB database realized a classification rate of 74%. The same system was extended [24] to classify gender, age and handedness from handwriting and was evaluated on the QUWI and KHATT databases. In addition to HOG, the authors also investigated the effectiveness of gradient local binary patterns (GLBP) [25] for characterizing gender from handwriting.

Based on the hypothesis that male and female writings offer visually distinct texture, we present a system for automatic classification of gender from handwriting using a set of textural features. A bank of Gabor filters (multiple orientations and scales) is applied to the handwriting images. The mean and standard deviation values of the response images are collected in matrix and the Fourier transform of the matrix is used as a feature to characterize gender from handwriting. Classification is carried out using an artificial neural network (ANN). The system is evaluated on the same database as the one used in the ICDAR 2015 competition on gender classification from handwriting [26], and realized promising classification rates. We first present a brief introduction to Gabor filters in Section II followed by feature extraction in Section III. Section IV presents the classification technique employed while the experimental results are discussed in Section V. Finally, the last section concludes the paper.

II. Gabor Filter

A Gabor filter is a sinusoidal plane of orientation and frequency modulated by Gaussian kernel [27]. It has been widely employed in a number of problems and is known to be very effective in capturing the textural information in an image. It is a linear filter and works similar to the human visual cortex. Different frequencies and orientations for different objects enable to find good responses for different textures. From the view point of images, the two dimensional Gabor filters proposed by Daugman [28] are mostly used where a pan of sinusoidal wave is created and then convolved with an image. This pan is of different sizes and orientations. Gabor function for two dimensional filter is defined as follows.

$$g(x,y;\lambda,\theta,\psi,\sigma,\gamma) = exp(-\frac{\acute{x}^2+\gamma^2\acute{y}^2}{2\sigma^2})cos(2\pi\frac{\acute{x}}{\lambda}+\psi)$$

Where:

$$\acute{x} = x\cos\theta + y\sin\theta\acute{y} = -x\sin\theta - y\cos\theta$$

In the above equation, x and y are the specified position of visual field in image, λ is the sinusoidal factor of the wavelength, θ is angle or orientation of parallel stripes generated in Gabor filter, ψ represents the phase offset, σ is the standard deviation of the Gaussian function while γ is defined as the aspect ratio in spatial domain which actually specifies the size of ellipse.

As mentioned earlier, Gabor filter is used widely for texture features extraction. Generally, a bank of Gabor filters is generated with different scales/sizes and orientations/angles. A bank of Gabor filter with 4 scales and 6 orientations is illustrated in Figure 1 [29].

After having discussed the general idea of Gabor filters, we present its application to feature extraction from handwriting images in the next section.

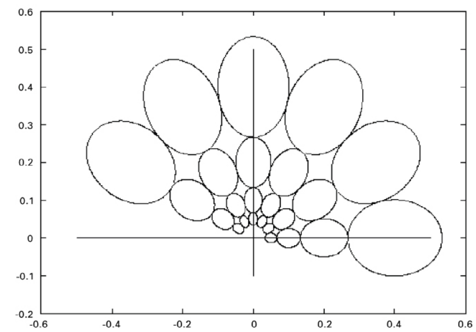

Fig. 1. Gabor Filter Bank of different Scales and Orientations [29]

III. Feature Extraction

Features are extracted by applying a Gabor filter bank on handwriting image and computing the mean and variance of each filtered image. The filter bank is generated for 6 orientations and 4 scales and the size of each filter is 39×39. The visual representation of the filter bank is shown in Figure 2 while the application of two of the filters in the bank to handwriting images is illustrated in Figure 3. The number of scales and orientations was chosen on a validation dataset and the effect of these parameters on overall system performance is discussed later in the paper.

After application of the filter bank to an image of handwriting, a total of 48 (4×6) response images are generated. We compute the mean value of each of the images and store these values in a 4×6 matrix. Likewise, a matrix of variance values is also produced. Fourier transform is then applied on each of the two matrices and the resulting response values are used as features. This produces a 96 dimensional feature vector that is used to characterize a handwriting.

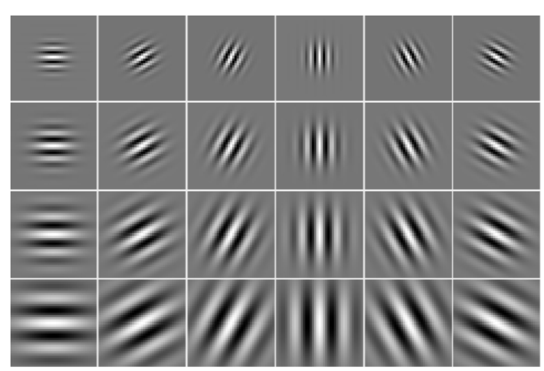

Fig. 2. Visual Representation Gabor Filter Bank with 4 Scales and 6 Orientations

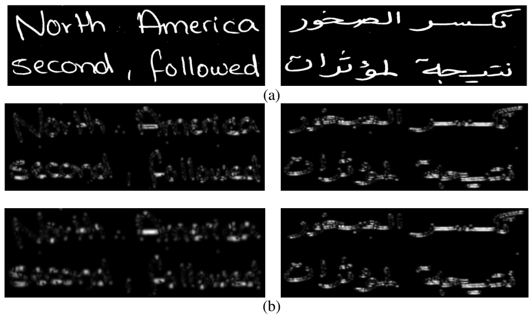

Fig. 3. Application of Gabor filters (a): Original Images (b): Response of two of the filters from the bank

IV. Classification

For classification, we have employed a feed forward artificial neural network. The features from writing samples of male and female writers in the training database are fed to the network making it learn to differentiate between the two classes. The number of hidden neurons in the network is chosen empirically using the validation dataset. During classification, the feature vector of the query writing image is fed to the trained network which outputs the class label, i.e. male or female writer.

In the next section, we present the experiments carried out to validate the effectiveness of the proposed technique.

V. Results

This section presents the results of the experiments carried out to evaluate the proposed technique. All experiments are carried out the QUWI handwriting database [30]. The database comprises handwriting samples of more than 1000 writers with 4 samples of each writer, 2 in Arabic and 2 in English. For comparison purposes, we employ the same experimental protocol as that of the ICDAR 2015 competition [26] on gender classification. The following four experimental scenarios are considered in our study.

- Task A: Arabic writing samples only.
- Task B: English writing samples only.
- Task C: Arabic samples in training and English samples in test.
- Task D: English samples in training and Arabic samples in test.

For each of the four tasks, 300 writing samples are used as training set, 100 as validation and 100 as the test set. The division of images into training, validation and test sets is the same as in ICDAR 2015 gender classification competition. The classification rates on the four tasks are summarized in Table I. It can be seen that classification rates of 70%, 67%, 69% and 63% are realized for the tasks A, B, C and D respectively.

We also compare the performance of our system with those realized by the participants of the ICDAR 2015 competition [26].The results of the participants on the four sub-tasks

TABLE I. Gender Classification Rates on Four Tasks

Task A	Task B	Task C	Task D
70%	67%	69%	63%

of gender classification problem are summarized in Table II. It can be seen from Table II that the proposed system realizes better classification rates than those of the winner systems in the competition under exactly the same experimental settings. It is also interesting to note that the performance of the system across different tasks is consistent with those listed in Table II. The highest classification rates are reported for Task A while Task D is the most challenging one where all systems report relatively low classification rates.

TABLE II. Results of ICDAR 2015 Gender Classification Competition ([26])

Method	Classification Rate (Rank)			
	Task A	Task B	Task C	Task D
LISIC	60(3)	42(8)	49(5)	55(2)
ACIRS	60(3)	54(3)	53(3)	49(6)
Nuremberg	62(2)	**60(1)**	55(2)	53(3)
MCS-NUST	47(7)	51(5)	48(6)	45(8)
CVC	**65(1)**	57(2)	**63(1)**	**58(1)**
QU	44(8)	52(4)	53(3)	47(7)
UBMA	51(5)	50(6)	44(7)	50(5)
ESI-STIC	48(6)	46(7)	42(8)	53(3)
Proposed Method	**70**	**67**	**69**	**63**

We also studied the effect of number of orientations and scales in the bank of Gabor filters on the overall classification rates. It can be seen from Figure 4 that the performance of the system on all four tasks is more or less consistent for different combinations of orientations and scales. Similar to the validation dataset, the highest classification rates are realized at 4 scales and 6 orientations on the test dataset as well.

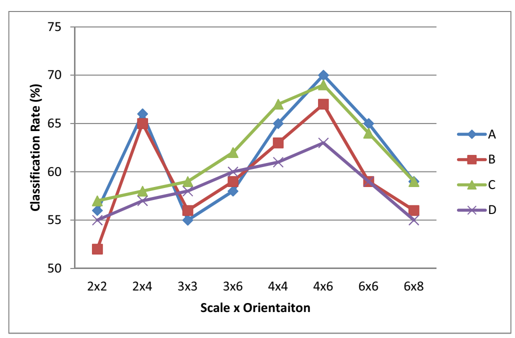

Fig. 4. Classification rates as a function of orientations and scales

VI. Conclusion

This paper presented an effective technique for classification of gender from offline handwriting images. The study is based on the hypothesis that male and female writings are visually distinct. We, therefore, exploit textural features to characterize gender from handwriting. A bank of Gabor filters (with multiple orientations and scales) is applied on the handwriting images and the mean and standard deviation of the filtered images are stored in a matrix. The Fourier transforms of these matrices are then used as features. The extracted features are used to train an artificial neural network which classifies the gender of the author of a query handwriting sample. The system evaluated on Arabic and English handwritings in the QUWI database realized high classification rates. A comparison with the classification rates realized in the ICDAR 2015 gender classification competition demonstrates the superiority of the proposed method over existing techniques.

Presently, we work on offline images of handwriting. It would be interesting to study the performance of gender classification on online handwriting samples where additional information like time spent, pen pressure, speed and other dynamic parameters are also available. We also intend to explore other textural features like fractal dimension, wavelets and other local textural descriptors for this problem. It would also be interesting to carry out a feature selection study to select the best set of features characterizing gender of the writer of a handwritten document.

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