Co-occurrence Matrix of Oriented Gradients for Word Script and Nature Identification

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***Abstract*—In this paper, we propose a new scheme for script and nature identification. The objective is to discriminate between machine-printed/handwritten and Latin/Arabic scripts at word level. It is relatively a complex task due to possible use of multi-fonts and sizes, complexity and variation in handwriting. In the proposed script identification system, we extract features from word images using Co-occurrence Matrix of Oriented Gradients (Co-MOG). The classification is done using *k* Nearest Neighbors (*k*-NN) classifier. Extensive experimentation has been carried on 24000 words extracted from standard databases. An average identification accuracy of 99.85% is achieved which clearly outperforms results of some existing systems.**

***Keywords*—*Script and nature identification; Word level; Co-occurrence Matrix of Oriented Gradients; K*-NN.**

I. Introduction

Machine-printed/handwritten document consisting of Arabic and Latin scripts is quite common. It is desirable to have systems capable of handling inputs in a variety of forms such as those documents. As OCRs are generally language dependent and document layout analysis is also sometimes language dependent, the need of script identification systems becomes obvious. Existing script identification techniques mainly depend on various features extracted from document images at block, text-line or word level. Block level script identification identifies the script of the given document in a mixture of various script documents. In text-line based script identification, a document image can contain more than one script but it requires the same script on a single text-line. Word level script identification allows the document to contain more than one script and the script of every word is identified.

In this paper, we propose to discriminate between machine-printed and handwritten words written in Arabic and Latin scripts. Note that script identification is a complex task due to possible use of multi-fonts and sizes, complexity and variation in handwriting. As the performance of script identification depends on the effectiveness of feature descriptor extracted from the word image, the feature should be informative enough. We propose to investigate the use of co-occurrence matrix of oriented gradients (Co-MOG) for the task of script identification. The main idea is to exploit the writing orientation as a discriminative descriptor for Arabic and Latin separation. For this, we rely on the observation that we made in the examination of the morphology of these two scripts. Letters in Arabic words, especially of handwritten nature or italic machine-printed and as written from right to left, are generally tilted to the left, following the writing direction (see Fig. 1(a)). In contrast, Letters in Latin script, especially of handwritten nature or in italic machine-printed and as written from left to right, tend to be inclined to the right (see Fig. 1(b)). Thus, Arabic letter strokes are generally diagonally down whereas those written in Latin are diagonally up. Furthermore, machine-printed Arabic words are characterized by the use of horizontal ligatures, more or less long depended on the used font (see Fig. 1(c)). Oppositely, machine-printed Latin words are composed by successive letters without any ligature between them (see Fig. 1(d)). Consequently, horizontal strokes would be more frequent in Arabic words than in Latin words. Note that both scripts use vertical strokes for ascenders. It is those observations that motivated us to explore how the spatial distribution of shape can benefit script and its nature identification. The rest of the paper is organized as follows.

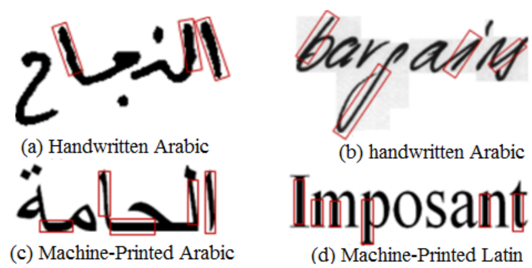

Fig. 1. Machine-printed/Handwritten and Arabic/Latin word identification based on the writing orientation.

Related literature work is given in Section II. The Section III describes useful discriminating features to identify the script and its nature at word level. The details of experimental results obtained are presented in Section IV. Conclusion is given at Section VI.

II. Related Literature Work

There are a number of techniques available for feature extraction to discriminate between machine-printed and handwritten Arabic and Latin scripts at word level. Haboubi and al. in [5] tested Gabor filters, gray-level co-occurrence matrices and wavelets separately for Arabic/Latin word identification. They only considered machine-printed words. In [4], Benjelil and al. proposed an identification system based on steerable pyramid transform. The features are extracted from pyramid sub-bands and served to classify the scripts on only one script among the scripts to identify. Mozaffari and Bahar [7] proposed to use the baseline profile features for

Farsi/Arabic handwritten/machine-printed words classification. In [9], Mezghani and al. considered affine moment invariants, the number and the XY position of the top and the bottom extrema, the maximal amplitude obtained from the difference between the top and the bottom profiles for Arabic/French and Handwritten/Printed words identification. In [10], Benjelil and al. present a performance comparison of curvelets, dual-tree complex wavelet and discrete wavelet transform in handwritten words classification (Arabic and Latin). In former works [1], [3], we successfully employed different sets of features such as word vertical projection variance, baseline profile, run-length and crossing count histograms, bottom diacritics, loop position and elongate descenders.

As it can be noted, global and local features of different types (structural, statistical, textural, etc.) are considered for the task of machine-printed/handwritten and Arabic/Latin word identification. But structural features are script dependent and frequency domain features (Gabor filters, wavelets transform, etc. which are not script dependent) are not proficient to work with small size images like word images. In fact, most of these features are not effective to capture differences between handwritten Arabic and Latin scripts especially due to their cursive nature. In recent work [2], we used pyramid histogram of oriented gradients to exploit the writing orientation and we achieved satisfactory results. But, we noted that including co-occurrence with various positional offsets, the features descriptors can express complex shapes of writing with local and global distributions of gradient orientations. That is why we propose, in this work, the use of co-occurrence matrix of oriented gradients.

III. Proposed System

In this paper, we focus on the feature descriptors. As diagramed in Fig. 2, the first two parts extract Co-MOG descriptors from input images, and then the last part classifies the given word image into one of four classes: PA(Printed Arabic), PL(Printed Latin), HL(Handwritten Latin) and HA(Handwritten Arabic) using *k*-NN classifier and outputs classification results.

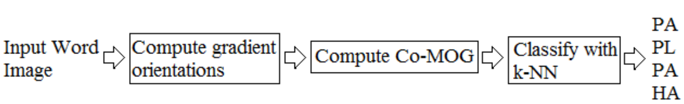

Fig. 2. Block diagram describing the steps involved in the method.

Note that Co-MOG is based on Histograms of Oriented Gradients (HOG). It calculates gradient in a local scale. Therefore, it is robust to illumination and deformations.

A. Histograms of Oriented Gradients (HOG)

The use of HOG as texture descriptor was introduced by Dalal and Triggs in 2005 [11] for human recognition. HOG descriptors are also used in some recent text recognizers by Minetto and al. in [12]. In this subsection, we firstly provide a detailed description of the basic HOG descriptor. In order to extract HOG from an image, firstly gradient orientations at every pixel are calculated. In particular, gradient image R of I is computed as $R = \{R_g, R_o\}$ where R_g and R_o being

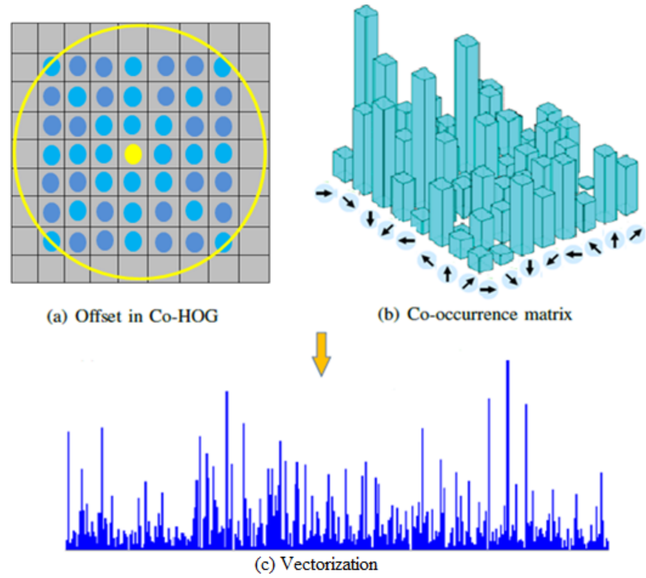

Fig. 3. (a) Offset in Co-MOG, (b) Co-occurrence of a word image at a given offset, (c) Vectorization of co-occurrence matrix [13].

respectively magnitude and orientation of gradient. Secondly, a histogram of each orientation in a small rectangular region is calculated. The orientation of pixels is quantized to n bins and a histogram of orientation is calculated at each bin as follows:

$$H(i) = \sum_{x,y \in I, R_o(x,y)=i} R_g(x,y), i = 1,..,n \qquad (1)$$

Next, the histogram is built by a concatenation of $H(i)$. In experiments, the interval $[0, 2\pi]$ is divided into $n = 8$ bins. Each bin covers an orientation range of $\frac{\pi}{4}$.

B. Gradient Information Capturing

The co-occurrence matrix can be used to express the distribution of gradient information over an image. We used co-occurrence HOG as proposed by Watanabe and al. [13] for human detection. In fact, this feature captures spatial information by counting the frequency of co-occurrences of oriented gradients between pairs of pixels. Thus relative locations are stored. The relative locations are reflected by the offset between two pixels as shown in Fig. 3(a). The offset $(\triangle_x, \triangle_y)$ specifies the distance between the pixel of interest and its neighbor. The yellow pixel in the center is the pixel under study and the neighboring blue ones are pixels with different offsets. Each neighboring pixel in blue color forms an orientation pair with the center yellow pixel and accordingly votes to the co-occurrence matrix as illustrated in Fig. 3(b). Therefore, HOG is just a special case of Co-MOG when the offset is set to $(0;0)$, that is only the pixel under study is counted. The frequency of the co-occurrences of oriented gradients is captured at each offset via a co-occurrence matrix as shown in Fig. 3(b). Compared with HOG, Co-MOG captures more local spatial information but at the same time keeps the advantage of HOG, i.e., the robustness to illumination variation and invariance to local geometric transformation.

In most other works, the authors proceed by dividing an image into blocks and extract matrices from each block. In our case, we consider the whole image without making use of block division. Given an image I of size $N * M$ where G is its gradient orientation matrix, the Co-MOG matrix P can be defined as follows.

$$P(i,j) = \sum_{x=1}^{N}\sum_{y=1}^{M}\begin{cases} 1, & \text{if } G(x,y)=i \;\; \& \; G(x+\triangle_x, y+\triangle_y)=j \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

Note that P is a square matrix and its dimension is $n * n$ where n is the number of orientation bins. The normalized Co-MOG matrix is denoted by $P_{ij}(d,\theta)$ where d is the displacement vector and θ is the angle.

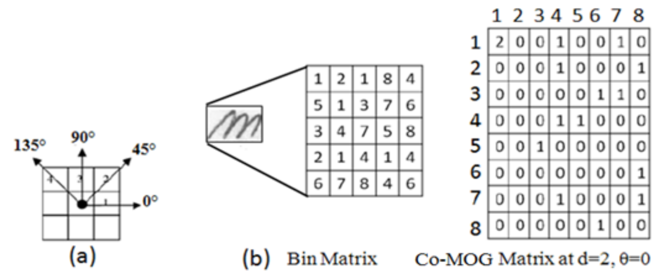

Fig. 4. (a) From the centered pixel (o); pixel 1 represents 0° at $d=1$; pixel 2 represents 45°; pixel 3 represents 90° and pixel 4 represents 135° at $d=1$; (b) Co-MOG matrix calculated at $d=2, \theta=0°$ for a 8 by 8 neighborhood around the pixel of interest.

IV. Experiments and Parameters Determination

A. Data

We consider here word images from four public databases: IAM database for Latin handwritten [14], IFN-ENIT [15] and AHTID/MW [16] for Arabic handwritten and APTI [17] for Arabic and Latin printed words. The training and test words have 24000 samples, consisting of equal number of Printed Arabic (PA), Handwritten Arabic (HA), Printed Latin (PL) and handwritten Latin (HL) words. Our experiments are performed using ten fonts for Arabic (Andalus, Arabic Transparent, AdvertisingBold, Diwani Letter, DecoType Thuluth, DecoType Naskh, Tahoma, Traditional Arabic, Simplified Arabic and M Unicode Sara) and ten fonts for French (Arial, Monotype Corsiva, ComicSansMS, Edwardian Script ITC, Times New Roman, French Script MT, Impact, Georgia, Arial Black and Tahoma). For simplicity and speed, we use *k*-NN classifier throughout the study and the Genetic search Algorithm which is an efficient dimensionality reduction technique [18]. To test the performance of the classifier, we use *n*-fold cross-validation and leave one out methods. Cross-validation is then repeated *n* times with all of the *n* sub-samples used exactly once as the validation data. The cross-validation estimation of accuracy is the overall number of correct classification divided by the number of instances in the data set. In our case, *n* is set to 10. For performance evaluation, accuracy criterion is defined as follows: Accuracy $= \frac{\text{Number of correctly classified words}}{\text{Number of words}}$.

B. Parameters of Co-occurrence Matrix optimization

There are four important parameters in co-occurrence matrix: the choice of angle, the dimension of matrix N, the horizontal and vertical offsets $\triangle_x$ and $\triangle_y$ (we set $\triangle_x$ equals to $\triangle_x$ for the purpose of simplification) and the type of gradients (signed or unsigned).

1) The choice of angle: Since Co-MOG expresses shapes in detail, it is high-dimensional. To be methodical in our case, we targeted the selection of angles in Co-MOG calculation according to the type of data (image writing). Thus, the numbers of Co-occurrence Matrix of Oriented Gradients calculations could be significantly reduced. We only compute Co-MOG on top half of reference pixel, considering just 4 angles (see Fig. 4(a)). So only four orientations are considered in computing co-occurrence matrices: 0°, 45°, 90° and 135°.

Arabic, as written from right to left, letters in words are generally tilted to the left, following the writing direction (a high number of pixel pair form an angle of 135°). In contrast, Latin script, as written from left to right, letters tend to be inclined to the right (a high number of pixel pair form an angle of 45°). Thus, Arabic letter strokes are generally diagonally down whereas those written in Latin are diagonally up. Furthermore, machine-printed Arabic words are characterized by the use of horizontal ligatures, more or less long depended on the used font (a high number of pixel pair form an angle of 0°). In contrast, machine-printed Latin words are composed by successive letters without any ligature between them. Letters tend to be vertical (a high number of pixel pair form an angle of 90°). Thus, horizontal strokes would be more frequent in Arabic words than in Latin words. Note that both scripts use vertical strokes for ascenders. It is these observations that motivated us to choose these four angles.

2) The dimension of matrix N and the offsets ($\triangle_x$, $\triangle_y$): The effect of dimension of matrix on the identification rate was also tested. Really the dimension of matrix N matching the number of orientation bins. In Arabic and Latin scripts (especially of machine-printed type) there are many letters which are simply composed of vertical strokes (e.g. the Arabic letters: ا and ل and the Latin letters: l, t, see Fig. 5(a)). In machine-printed Arabic, letters are horizontally ligated and ligatures may be more or less long according to the used font (some fonts allow letter elongations, see Fig. 5(a)). So for these letters and horizontal ligatures, many neighboring pixels have the same directions. In these cases, a far distance could be enough to characterize letter strokes without loss of information since there is no morphological variation. As against, in the case of cursive writing (Arabic and handwritten Latin scripts), where letters are not necessarily rectilinear (e.g. 'r', 'e', 'c', 'o', etc. see Fig. 5(b), the use of a near distance is obvious to better describe letter shapes (e.g. bends, loops, angles, stems, legs, etc.). One should choose the best offset which considers any morphological change in letters. For this reason, we tested with 7 different offsets (from 1 to 7 as shown in Fig. 6).

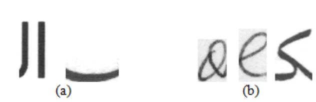

Fig. 5. (a) Simple shape letters, (b) Complex shape letters.

The identification results are illustrated as Fig. 6. The best dimension of co-occurrence matrix is 9 achieving 99.85%

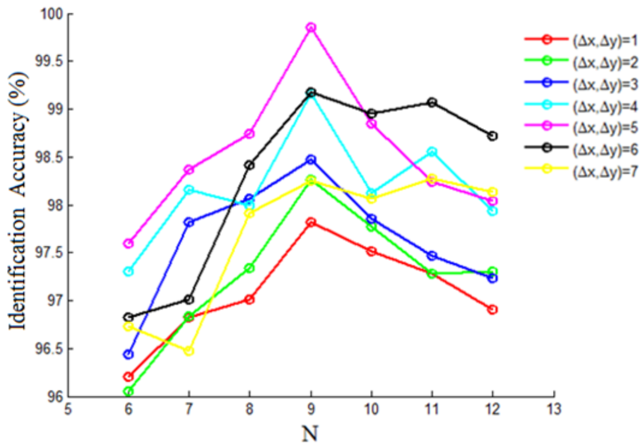

Fig. 6. Co-occurrence matrix parameters optimization. $\triangle_x$ and $\triangle_y$ are the horizontal and vertical offsets of co-occurrence matrix respectively, and N is the dimension of co-occurrence matrix.

in identification accuracy and the best offset is 5 in both horizontal and vertical direction.

3) Signed/unsigned gradients: The gradient orientation is used to determine the corresponding coordinate of a pair of gradient pixels in co-occurrence matrix, and the experimental results show that the signed gradient (0°-360°) performed better than the unsigned gradient (0°-180°), achieving 99.85% comparing to 97.52% in identification rate.

C. Parameters of Co-occurrence Matrix Normalization

The normalization of co-occurrence matrix is essential before comparison. Four types of normalization methods were compared by Dalal [11] to get HOG feature, and these methods are also adopted to normalize co-occurrence matrix. Let v be the co-occurrence matrix, $\|v\|_k$ be the *k-norm* where $k = 1, 2$ and ϵ be a small constant. The four normalization methods are: (1) *L1-norm*, $v \rightarrow \frac{v}{(\|v\|_1+\epsilon)}$; (2) *L1-sqrt*, $v \rightarrow \sqrt{\frac{v}{(\|v\|_1+\epsilon}}$; (3)*L2-norm*, $v \rightarrow \frac{v}{\sqrt{\|v\|_2^2+\epsilon^2}}$; (4)*L2-Hys*, $v \rightarrow \frac{v}{\sqrt{\|v\|_2^2+\epsilon^2}}$, $max(v) = 0.2$.

Table I gives the comparative performance of these normalization methods, and the non-normalization result is also listed in this table. Note that the best normalization method for co-occurrence matrix is the *L2-Hys* based on the results of Table I.

TABLE I. COMPARATIVE PERFORMANCE OF 5 KINDS OF NORMALIZATION METHODS.

Normalization Type	Accuracy(%)
Non-Normalization	96.87
L1-norm	98.65
L1-sqrt	99.24
L2-norm	98.29
L2-Hys	99.85

Up to now, we have determined all parameters of Co-MOG. In summary, the parameters to calculate the Co-MOG are as follows: 9×9 co-occurrence matrix, 5 pixels offset in both horizontal and vertical direction, signed gradient (0°-360°) and *L2-Hys* co-occurrence normalization. The dimension of the final Co-MOG descriptor is equal to $9 * 9 * 4 = 324$.

D. Classification and features selection

As explained in the previous section, a total of 324 features are extracted from each word image. The total number of the extracted Co-MOG features is rather high. Also, these features are likely irrelevant and redundant. Genetic Algorithm (GA) and Principal Component Analysis (PCA) were applied for reducing the dimensionality of the feature vectors. When applying PCA, the number of features is reduced from 324 to 161 and to 248 if GA is used.

E. Identification with different classifiers

The obtained feature vectors are fed into *k*-NN, SVM and Bayes (AODEsr) as shown in Table III. The *k*-NN is the extension of the Nearest Neighbor classifier: An unknown word is classified by assigning it the label most frequently represented among the *k* nearest word samples. A decision is made by examining the labels of the *k* nearest neighbors and taking a vote. An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall on as explained by Cortes and Vapnik [21]. AODEsr (Aggregating One-Dependence Estimators with Subassumption Resolution) is a probabilistic classification learning technique which was developed to address the attribute-independence problem of the popular Bayes classifier as noted by Lu and al. [6].

As it can be seen *k*-NN with GA features selection method, provides good results in comparison to the others classifiers. An average identification Accuracy of 99.85% is achieved. Note that handwritten Latin words are correctly identified in 100% of cases. To highlight the usefulness of features selection step, we compared the obtained results with those from a random forest classifier which proceeds without features selection and we found that it achieves an identification rate of 96.74% which is clearly inferior to 99.85%. Table III shows identification Accuracy by class when using *k*-NN.

When observing the confusion matrix (see Table II), we note that it is about confusion cases between Printed Latin and Arabic scripts due to the use of multi-font printed words that cover various complexities of shapes. For example, “French Script MT” is among the used fonts in the construction of our database (see Fig. 7(a)). This font is characterized by a connection between the characters in the word contrary to other commonly used fonts and by the vertical tendency of ascending and descending. It is true that there are several fonts where the letters are connected but the orientation of the characters is to the right as the “Edwardian Script TC” font (see Fig. 7(b)). So in our case, the misclassified words of printed Latin class are the words with many letters linked together which belong to the “French Script MT” font. On the other hand, there are some confusion between the printed Arabic and the printed Latin scripts. This error rate is due to the short length of some words with disconnected and vertically oriented letters (see Fig. 7(c)).

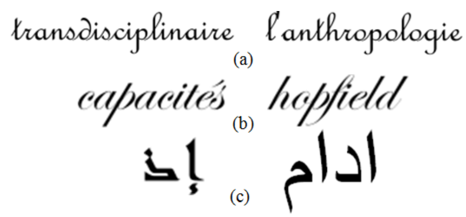

Fig. 7. (a) Some cases of machine-printed Latin words are classified as machine-printed Arabic words, (b) ,(c) Some cases of machine-printed Arabic word are classified as machine-printed Latin words.

TABLE II. CONFUSION MATRIX.

	PA	HA	PL	HL	Accuracy(%)
PA	5982	0	18	0	99.70
HA	0	6000	0	0	100
PL	16	0	5983	1	99.71
HL	1	0	0	5999	99.98
				Average	99.85

TABLE III. ACCURACY BY CLASSIFIER, USING DIFFERENT FEATURES SELECTION METHODS.

	Co-MOG with GA (%)	Co-MOG with PCA (%)
SVM	96.43	96.27
k-NN	**99.85**	98.95
AODEsr	99.71	98.07

F. Comparing with some identification systems

We compared Co-MOG (our proposed system) with systems proposed by Benjelil and al. in [4] and Mezghani and al. in [9] which deal with the same problem. To compare Co-MOG with the steerable pyramid transform, proposed in [4] work, we used a common database (our database composed of 24000 word samples). Table 12 summarizes the obtained results. Notice that when testing with steerable pyramid transform [8], as done by Benjelil and al. in [4] but on a larger database (20000 words instead of 800 words), the identification accuracy was increased from 97.5% to 98.94%. As it can be seen, the use of Co-MOG features with k-NN classifier achieves an accuracy of 99.85% which is clearly better than 98.94%. We also compared our system to the one proposed by [9] on their database (20000 words) then on our own database (24000 words). We noted a significant improvement in the identification Accuracy (99.85%) which demonstrates the merits of the proposed system.

TABLE IV. COMPARING WITH SOME IDENTIFICATION SYSTEMS.

System	Features Number	Classifier	Database	Accuracy(%)
[4]	48	k-NN	800	97.5%
[8]	48	k-NN	24000	98.94%
[9]	64 per window	GMMs	20000	99.10%
Co-MOG	226	k-NN	20000	99.76%
Co-MOG	**248**	k-NN	**24000**	**99.85**%

V. CONCLUSION

In this paper, a new method to discriminate between machine-printed/handwritten and Arabic/Latin words is presented. The proposed method is developed based on the distinct features of the Co-MOG extracted from word image. It emphasizes the significance of directional information for word script identification. It is robust to varied image sizes and different styles of writing. In training samples, we handled with different word fonts and sizes because in reality there are many fonts for the same script. The k-NN classifier is used to classify the test sample. The method looks simple, as it does not require any character or word segmentation. Experimental results demonstrate that relatively simple technique can reach recognition accuracy of 99.85% for a set of words constructed from standard databases.

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