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Arabic Handwritten Script Recognition System Based on HOG and Gabor Features

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Abstract: *Considered as among the most thriving applications in the pattern recognition field, handwriting recognition, despite being quite matured, it still raises so many research questions which are a challenge for the Arabic Handwritten Script. In this paper, we investigate Support Vector Machines (SVM) for Arabic Handwritten Script recognition. The proposed method takes the handcrafted feature as input and proceeds with a supervised learning algorithm. As designed feature, Histogram of Oriented Gradients (HOG) is used to extract feature vectors from textual images. The Multi-class SVM with an RBF kernel was chosen and tested on Arabic Handwritten Database named IFN/ENIT. Performances of the feature extraction method are compared with Gabor filter, showing the effectiveness of the HOG descriptor. We present simulation results so that we will be able to prove that the good functioning on the suggested system based-SVM classifier.*

Keywords: *SVM, arabic handwritten recognition, handcraft feature, IFN/ENIT, HOG.*

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1. Introduction and Related Works

Being a part of the larger domain of pattern recognition and mainly because it is a challenging matter, Arabic handwritten script recognition has been profoundly studied for decades in the handwriting recognition area. Various algorithms as Support Vector Machine (SVM), Artificial Neural Networks (ANN) and Hidden Markov Model (HMM), etc., have been exploited by researchers who have attained a lot of favorable results.

On the other hand, SVM classifier [27] has been successfully and largely used in various domains [4, 16, 17] like pattern recognition, pattern classification and image processing in order to solve the different problems such as regression, classification, etc.

Having supplied survey applications pattern recognition and exploiting SVM, Byun and Lee [5] examined types which are related to their objectives such as object recognition, handwritten character/digit recognition, face detection, face verification and many others. Similarly, Chen et al. [7] introduced a recognition system by using SVM. They showed the more efficiency of Gabor features than those previously studied and more than feature techniques. In [12], Elleuch et al. investigated Multi-class SVM for Arabic handwritten script recognition with Offline Handwritten Arabic Characters Database. The proposed system takes the hand-crafted feature as input and proceeds with a supervised learning algorithm. It is noticeable that the experimental study has efficiently showed that they have excellent outcomes if compared to the state-of-the-art Arabic OCR.

Recently using local gradient feature descriptors for handwritten character recognition Surinta et al. [26] to assess these features descriptors and classifiers on three different language scripts, especially Bangla, Thai, and Latin. They succeeded to get a highly working recognition using a simple classifier like k-nearest neighbor method and they even obtained very high recognition accuracies once exploiting a support vector machine classifier.

Still, building good and robust features represents a further challenge in object detection, hand gesture and pattern recognition [22, 19, 25, 24]. Especially in handwritten script recognition problem, many proposed/developed systems have based on the feature extraction methods such as Invariant Moments, Gabor filter, Gradient-Structural-Concavity, pixel intensities, Histogram of Oriented Gradients and Scale Invariant Feature Transform descriptor, and achieving acceptable/good results. Therefore, the choice of these hand-crafted features defines the performance of systems applied for classification and recognition.

Due to the high variety and complexity of Arabic handwritten - different strokes, shapes and concavities - we have selected Histogram of Oriented Gradients (HOG) descriptor which is robust to local displacements, yet still supply discriminative feature vectors as figuration of the handwritten characters [26]. Then, feature vectors obtained by this Feature extraction technique is combined with the SVM classifier to make classification. Figure 1 presented our suggested system architecture including the pre-processing steps, and then hand-crafted feature extractor using HOG and Gabor features. Finally, the handwriting recognition is performed by SVM Classifier.

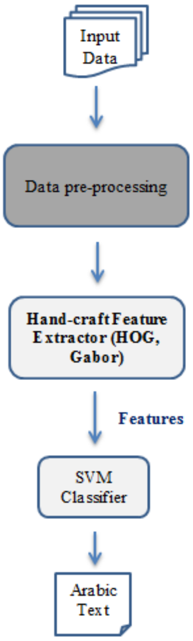

Figure 1. Proposed system overview

This paper is organized in the following way. Section 2 presents briefly SVM classifier. We evaluate the performance of the proposed descriptors in section 3. Finally, we present the concluding remarks and some future works in section 4.

2. Support Vector Machine (SVM)

SVMs are techniques of supervised learning based on the statistical learning theory of Vapnik [27] and Cortes [9]. The SVMs are binary classifiers intended to solve the problems of discrimination or regression. These classifiers are proving particularly effective, since they can deal with problems involving large numbers of descriptors. They allow to ensure a unique solution (absence of local optimum), and to provide good results on real problems [3].

3.1. Binary SVM

Let us suppose that we have a sequence X of observations $x_1 \ldots x_N$, described by measures on a predefined set of attributes, with N is the number of prototypes of programming, each of these observations being assigned to a class Y taken in $\{y_1, y_{-1}\}$. When an observation is provided as input to a perceptron, it produces a response which indicates only if this observation is on the side of the class "+" (output 1) or on the side of the class "-" (output -1):

$$\mathrm{w\,x-b}\begin{cases}\geq 0 \Rightarrow h(\mathrm{x})=1\\ <0 \Rightarrow h(\mathrm{x})=-1\end{cases} \qquad (1)$$

3.2. Linear SVM

Assuming that there are hyper-plans of equation $h(x)=wx-b$ used to separate the positive examples of negative examples. We will seek the optimal hyper-plane. After any a study by [8], and using the Lagrange multipliers α_i , the system of these hyper-plans resulting is:

$$\begin{cases}\max \alpha = \{\sum_{i=1}^{N}\alpha_i - \frac{1}{2}\sum_{i,j}^{N}\alpha_i\alpha_j y_i y_j (x_i, x_j)\}\\ \alpha_i \geq 0, i=1,\ldots,N\\ \sum_{i=1}^{m}\alpha_i y_i = 0\end{cases} \qquad (2)$$

The optimal separating hyper-plane can then be written as:

$$h(x)=(w^* x)-b^* = \sum_{i=1}^{m}\alpha^*{}_i y_i (x_i x)-b^* \qquad (3)$$

Where α^* is the solution to the previous equation and b^* is obtained by using any example critical (x_c, y_c) in the equation:

$$b^* = w^* x_c - y_c \qquad (4)$$

3.3. Non-linear SVM

The classifier to maximum margin that we just present allows to obtain good results when the data are linearly separable. Naturally, a large number of data sets are not linearly separable. Therefore, choose the borders of linear decisions seem to be a limiting factor. However, such models can be considerably enriched in projecting the data into a high-dimensional feature space and categorized utilizing a nonlinear transformation. This transformation was performed by kernel functions $k(x,x_i)$.

This function $k(x,x_i)$ allows to translate the optimization problem as follows:

$$\begin{cases}\max \alpha = \{\sum_{i=1}^{N}\alpha_i - \frac{1}{2}\sum_{i,j}^{N}\alpha_i\alpha_j\, \mathrm{k}(x_i, x_j)\}\\ \alpha_i \geq 0, i=1,\ldots,N\\ \sum_{i=1}^{m}\alpha_i y_i = 0\end{cases} \qquad (5)$$

Whose solution is the hyper-plane separator of equation:

$$h(x) = (w^* x) - b \;= \sum_{i=1}^{m} \alpha^*{}_i y_i \,\mathrm{k}(x_i x) - b^* \qquad (6)$$

Where the coefficients α_i^* and w^* are obtained as previously.

3.4. Kernel function

The appearance of the kernel functions has been able to overcome the limitation of linear separation. There are few types of functional kernel in the table below.

Type of kernel function	Equation
Linear kernel (simple scalar product)	$k(x, x_i) = x * x_i$
Radial Kernel Basis function (RBF)	$k(x, x_i) = e^{-\gamma \lVert x - x_i \rVert^2}$
polynomial Kernel	$k(x, x_i) = (x * x_i + c)^2$
sigmoid Kernel	$k(x, x_i) = \tanh(x * x_i + c)$

3.5. Multi-class SVM

The SVM have been primarily designed to resolve the problems of classification binaries. However several approaches have helped to broaden this algorithm to cases to N classes. In particular the two strategies are: one-versus-one (OVO) and one-versus-all (OVA)

- *The strategy one-versus-one (OVO):* In this strategy, all classifiers possible binary are designed by putting each class against another. The class the most trusted by classifiers will be an assignment (N classes => N (N-1)/2 Classifier).
- *The strategy one-versus-all (OVA):* In the strategy "one-versus-all", is opposed to each class "i" to "N-1" other classes. It then performs the assignment to the classifier who presents a maximum margin (N Classes => N classifiers.)

3. Experimental Results and Discussion

To recognize offline Arabic character, we carried out our experimental researches exploiting SVM classifier. The proposed system was tested on IFN/ENIT database [23]. The results are detailed and discussed in the next subdivision.

4.1. IFN/ENIT database

The IFN/ENIT database consists of 26459 Arabic words handwritten by more than 411 different writers, made up of about 115420 parts of Arabic words (PAWs) and about 212167 characters. The words written are 946 Tunisian town/village names. The data processing consists of offline handwritten Arabic words. The images are divided into 4 sets (a-d). There is one of the most commonly utilized databases, thanks to its largest size. Figure 2 shows samples of words, written by different writers.

In this study, words of IFN/ENIT database are segmented manually into letters from set (a) and (b). Our new Dataset based characters has 3752 samples including 2800 training samples and 952 test samples. The number of character per-class is around 67 (See Table 1). Obtained images have normalized to a gray-scale image of 28 × 28 pixels.

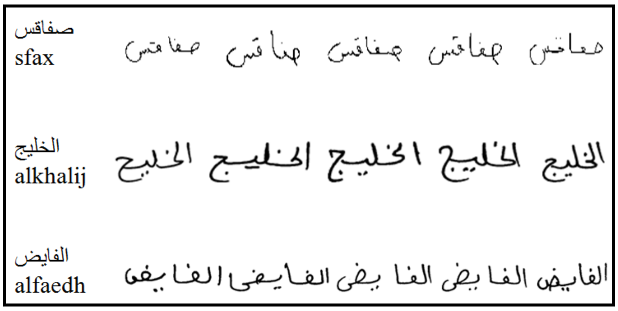

Figure 2. Samples from the IFN/ENIT database written by 5 different writers.

Table 1. Class for each shape of an Arabic script

Class	Image of character	Arab pronunciation	French pronunciation
1		ـا	Alef
2		ع	‘Ayn
3		ـب	Ba’
4		ـد	Dal
5		ـف	Fa
6		ح	Hha’
7		ـه	Ha
8		ـل	Lam
9		لا	Lam-alef
10		ـم	Mim
11		ـن	Nun
12		ـق	Qaf
13		ـر	Ra
14		ـص	Sad
15		ـس	Sin
16		ـو	Waw

17		ـي	Ya
18		عـ	‘Ayn
19		بـ	Ba
20		فـ	Fa
21		حـ	Hha’
22		هـ	Ha
23		لـ	Lam
24		كـ	Kaf
25		مـ	Mim
26		صـ	Sad
27		سـ	Sin
28		طـ	Tah
29		ا	Alef
30		ع	‘Ayn
31		د	Dal
32		ف	Fa
33		ح	Hha’
34		ه	Ha
35		ک	Kaf
36		ل	Lam
37		لا	Lam-alef
38		م	Mim
39		ن	Nun
40		ر	Ra
41		ص	Sad
42		س	Sin
43		و	Waw
44		ي	Ya
45		ء	Hamza
46		ـعـ	‘Ayn
47		ـبـ	Ba’
48		ـفـ	Fa
49		ـحـ	Hha’
50		ـهـ	Ha
51		ـلـ	Lam
52		ـكـ	Kaf
53		ـمـ	Mim
54		ـصـ	Sad
55		ـسـ	Sin
56		ـطـ	Tah

4.2. Experiments setting

For the purpose of evaluating the efficiency of the proposed system based on SVM classifier, we inquired its working performance to train and recognize characters of IFN/ENIT database as well as giving the technical implementation details of the adopted system in the next sub-section.

In order to get better character images and for IFN/ENIT after words segmentation; pre- processing entails binarization, noise reduction and filtrating the input text image as well so that we will be able to the enhance the image quality. As for feature extraction, Histogram of Oriented Gradients (HOG) descriptor [10] is utilized in this experiment and compared with Gabor filter [11, 18]. Finally, for the parameters setting, we have to define the optimal penalty and kernel parameter of SVM (σ and C).

4.3. Experiments using SVM model

In our experiments, we inquired the working of the SVM method for training and recognizing Arabic characters. For the setting architecture, we require to define about SVM classifier mainly two parameters of the RBF kernel; C and Sigma (σ). Because it enables us to get a more valuable discrimination than the linear kernel, we exploited the one-versus-all method with 56-way for the multi-class RBF kernel SVM with a less parameter than that of the polynomial kernel. For this purpose libSVM toolbox is utilized [6].

On the other hand, to show the importance of selecting the histogram of oriented gradients (HOG) descriptor for Arabic handwritten character recognition, we have compared them to representations/features of handwritten based on Gabor features.

In this work, HOG descriptor as a feature extraction method used to extract feature vectors which are then presented to a machine learning algorithm to do classification. Yet, in order to know the unrevealed handwriting text, the SVM presumes the handcraft features in the role of a feature vector and hence by scrutinizing the error classification rate on the Arabic handwritten character classification task.

Many parameters were used in order to evaluate the performance of the HOG descriptor. The parameters of the HOG descriptor contain the sub-region or block size, the cell size and the number of orientation bins. In our experiment, the optimal values adopted for each of the settings are: block size is 3×3 in the handwritten character images of size 28×28 and the orientation histograms consisting of 9 bins, given 81 ($3 \times 3 \times 9$) features for HOG descriptor.

For the Gabor filter experiments, the parameters are: 16 Gabor Filters was defined; we have chosen 4 frequency values, $f_1 = 2, f_2 = 4, f_3 = 8, f_4 = 16$, and 4 values for orientations ϕ between 0 and $3\pi/4$ equidistant from $\pi/4$(i.e. 0°, 45°,90° and 135°).

For each value of f and ϕ, two features can be extracted each time; mean and standard deviation, to save a feature vector with 32 elements.

We reported that in our experiments, RBF as a kernel function is used with C = 1 and σ = 1/k with k means the number of features in the input data.

The proposed recognition system based on RBF kernel SVM already described furnish an error classification rate (ECR) of 1.51% equal to 15 misclassified characters on the testing dataset with 56 classes using HOG descriptor while SVM with Gabor filter achieved an ECR of 7.16% corresponding to 68 misclassified characters. Figure 3 shows ECR for each class or character shape using HOG and Gabor features.

Table 2. ECR to our suggested systems applied on IFN/ENIT Database

Approaches	ECR
	IFN/ENIT database (56 classes)
HOG + SVM	**1.51 %**
Gabor Filter + SVM	7.16 %

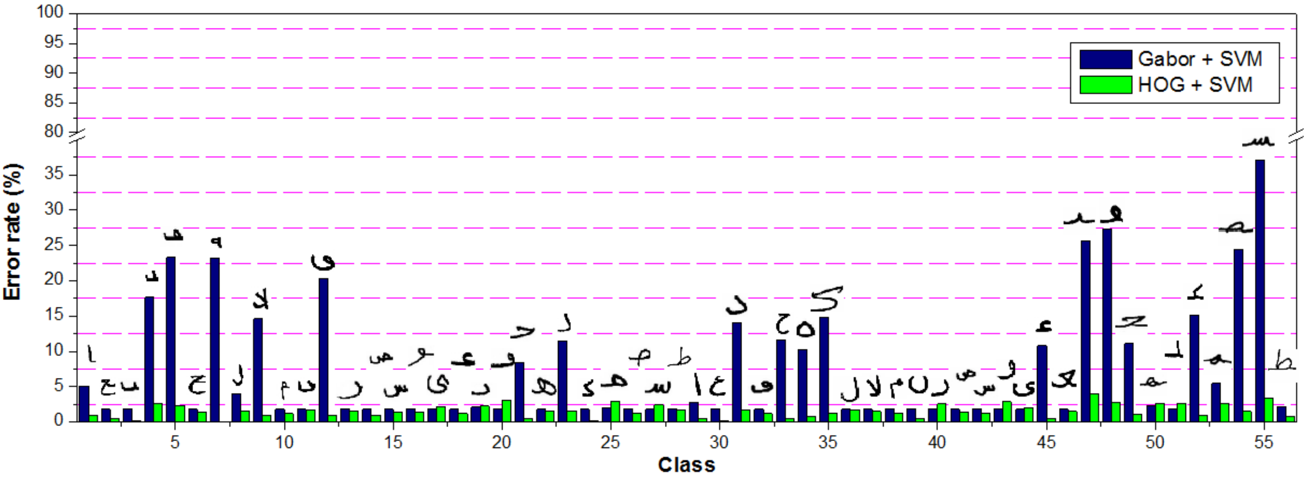

Figure 3. Character error rate for each class using HOG and Gabor features.

4. Discussion and conclusion

We brought together our proposed system with some other already proposed techniques. Using histogram of oriented gradients (HOG) method, SVM was revealed in table 2 to be acting more effectively than Gabor method when it is tested on the selfsame database IFN/ENIT. What was obvious was the notable profit in error classification rate (ECR) if compared to Gabor filter where we enhanced the entire identification rate by 5.65% with the proposed RBF kernel SVM exploiting HOG method. The current outcome, which showed the efficiency of our proposed system once it was compared with character recognition reliabilities got from state-of-the-art OCR systems, proved that HOG descriptor got the accuracy of 98.49% (see table 3).

Other techniques using handwritten Arabic database (see Table 3) were compared to our realized study of our proposed system. It was noted that our SVM model with RBF kernel exploiting HOG techniques for feature extraction step were still working more efficiently than hand-crafted features-based approach like ANN [20], HMM [2] and SVM [7, 12] methods and automatic method of feature extraction such as CNN [15] and CNN based-SVM [13, 14].

Table 3. Comparative results utilizing Arabic handwritten characters Databases

Authors	**Methods**	**Databases (class)**	**ECR**
Our work	**SVM + HOG** SVM + Gabor filter	IFN/ENIT (**56**)	**1.51 %** 7.16 %
Azeem et al [2]	HMM	IFN/ENIT	7 %
Elleuch et al [13]	CNN based-SVM	IFN/ENIT (**56**)	7.32%
Elleuch et al [14]	CNN based-	HACDB [21]	6.59%

	SVM	(**66**)	
Elleuch et al [12]	SVM + Gabor filter	HACDB (**66**)	11.23%
Lawgali et al [20]	ANN	Arabic characters (old version of HACDB)	21.18% (5600 shapes)
Elleuch et al [15]	CNN + raw data	HACDB (**66**)	14.71%
Chen et al [7]	SVM + Gabor filter	AMA Arabic Dataset (**34**) [1]	17.3%

In conclusion, we can say that our proposed system is working better than any other current approaches as it produces superior outcomes. RBF kernel SVM exploiting HOG method is totally a promising classification method in the handwriting recognition area. As perspective, we have to combine HOG and gabor features with a further feature vectors in order to increase the recognition rate.

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