Multi-stage Off-line Arabic Handwriting Recognition Approach using Advanced Cascading Technique

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Abstract: Automatic Recognition of Arabic Handwriting is a pervasive field that has many challenging complications to solve. Such complications include big databases and complex computing activities. The proposed approach is a multi-stage cascading recognition system bases on applying Random Forest classifier (RF) to construct a forest of decision trees. The constructed decision trees split big databases to multiple smaller data-mined sets based on the most discriminating computed geometric and regional features. Each data-mined set include similar database classes. RF match each test image with one of the data-mined sets. Afterwards, the matching classes are sorted relative to test image using Pyramid Histogram of Gradients and Kullback-Leibler based ranking algorithm. Finally, the classification process is applied on the highly ranked matching classes to assign a class membership to test image. Adjusting the classification process to only consider the highly ranked database classes reduced the computing classification and enhanced the overall performance. The proposed approach was tested on IFN-ENIT Arabic database and achieved satisfactory results and enhanced sensitivity of decision trees to reach 93.5% instead of 86.5% (Ghanim et al., 2018).

1 INTRODUCTION

Automatic Arabic Handwriting recognition is a challenging computer vision application. It is useful for analyzing and digitizing handwritten documents, reserving and documenting old manuscripts. It requires building robust hybrid classifiers that merge different but complementary methods to achieve high automatic recognition rates.

Handwritten recognition process is categorized into online or offline process(Amin, 1998). Offline recognition is based solely on visual images and pixel information which is more challenging and concerned in our work.

Arabic is a cursive language and one of the major worldwide document sources (Amin, 1998). Language specifications and description are provided by (Abandah and Khedher, 2009) and (AbdelRaouf et al., 2008). It is the native language of more than 420 million people around the world, the sixth most spoken language, and used in around 27 different languages (Campbell and Grondona, 2008) and can be represented in different handwriting styles.

The proposed approach is divided into three cascaded stages. The first is matching each test image with set of database classes. The second is ranking the set of matching classes and finally classification as described and analyzed in Section 3.In the introduced approach, recognition is done without character segmentation to decrease computing time and errors due to wrong segmentation.

Previous related work is summarized in section 2. The approach is described in section 3. The experiments and analysis of achieved results are proposed in section 4 . Conclusion and Future work are finally in sections 5 and 6.

2 LITERATURE REVIEW

Lawgali (Lawgali, 2015) provided a survey on Arabic handwritten automatic recognition. (Ghanim et al., 2018) summarized the different applied classifiers in this research area.

Hidden Marcov Model (HMM) was applied by (Hicham et al., 2016), (AlKhateeb et al., 2011), (Jayech et al., 2015) and (Dreuw et al., 2011) on IFN/ENIT Arabic database (Pechwitz et al., 2002).

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Localized density features and statistical-type features (Hicham et al., 2016) were extracted achieving 78.95% recognition rate. Intensity features on mirrored word image (MWI) (AlKhateeb et al., 2011) were extracted and achieved 86.73% success rate without re-ranking and 89.24% with re-ranking. Statistical and structural features (Jayech et al., 2015) achieved 91.1% recognition rates. Multi-Stream Hidden Markov Model was applied for handwriting recognition (Mezghani et al., 2014) using Gaussian Mixture Models (GMMs) to recognize Arabic and French handwritten words.

Support Vectored Machines (SVMs) achieved effective results in this field when applied on the IFN/ENIT database. (Elleuch et al., 2016) applied convolution neural network (CNN) and SVM to classify only 56 classes with error rate 7.05%. (Al-Dmour and Abuhelaleh, 2016) proposed a multi-stage model using SURF feature descriptor and K-means clustering algorithm to recognize 85% using SVM. (Khaissidi et al., 2016) applied Histograms of Oriented Gradients (HoGs) with SVM on Ibn-Sina dataset (Moghaddam et al., 2010).

(Saïdani and Echi, 2014) extracted a combination of Pyramid HOG and co-occurrence Matrix of HOG. (Elfakir et al., 2015) extracted HOG features using Sobel edge detectors. SVM was applied on the normalized features for classification.

Different types of Neural Networks (NN) were applied in this area. Pseudo-Zernike moments features (Leila et al., 2011) with Fuzzy ARTMAP neural network classified 96 word classes written by hundred writers with 93.8% recognition rate. (Lawgali et al., 2014) extracted Discrete Cosine Transform (DCT) features and applied Artificial Neural Network to classify a subset of IFN/ENIT database with 90.73% accuracy. (Benjelil et al., 2012) used a steerable pyramid decomposition method with k-NN classifier and achieved 97.5% success rate on a database of 800 printed and handwritten words.

Random forest (RF) was applied for handwriting recognition. (Shamim et al., 2018) presented a comparative study for offline digit recognition and SVM with RF classifier achieved highest results. (Do and Pham, 2015) computed GIST features with RF on USPS, MNIST data-sets. (Zamani et al., 2015) applied RF and convolutional neural network (CNN) for Persian handwritten digit recognition. The system was tested on Hoda data-set (Khosravi and Kabir, 2007). The concept of cascading classifiers was applied on different recognition problems and achieved satisfactory results (Ghanem et al., 2009), (Mohamed et al., 2018).

3 THE PROPOSED APPROACH

In the proposed approach three main consecutive stages are applied as presented in Figure 1. All stages are complementary to each other. The output of each stage passes as an input to the next subsequent stage. Each stage passes smaller set of chosen training classes to its next consecutive stage. Reducing number of concerned database classes per stage eases the classification task and equate classifier growing complexity.

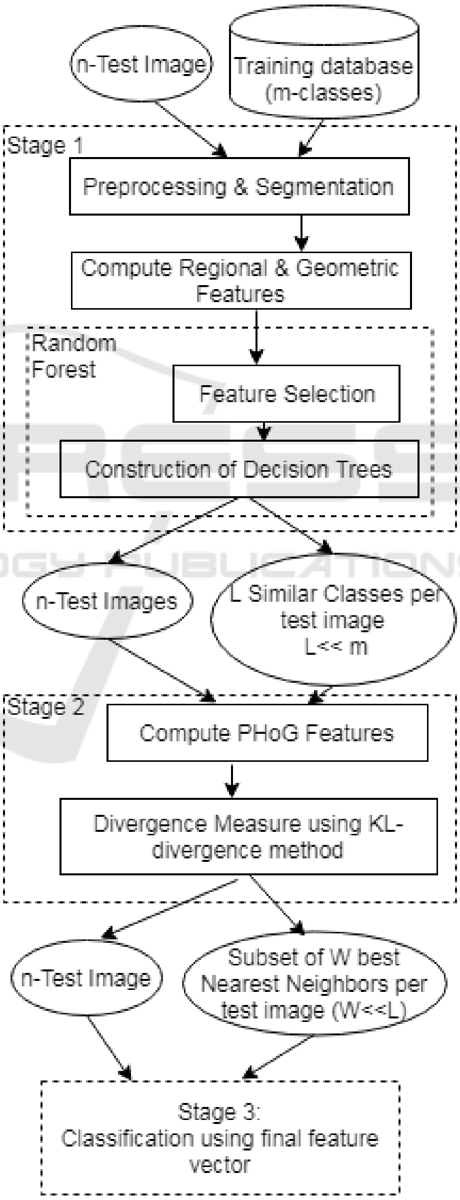


Figure 1: The proposed system overview.

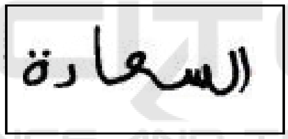
3.1 Stage 1: Matching Test Image with Similar Database Training Classes

This stage match each test image with a set of similar database classes. First, preprocessing and segmentation are applied (section 3.1.1), a set of features (Dileep, 2012) are then computed (section 3.1.2). Random Forest classifier vote for the optimum set of computed features and match each test image with a set of database classes. Matching sets include similar database classes together and is represented by a defined range of selected feature values. This introduces a data-mined database.

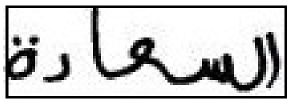
3.1.1 Preprocessing and Segmentation

The first stage starts by passing each test image and training database classes through preprocessing and segmentation as shown in Figure 1. It is an essential stage for consistent post analysis and classification.

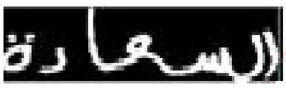
Images are binarized, cropped, normalized and thinned to one pixel wide to remove variations in handwritten images as shown in Figure 2. Binarization concentrates computations on regions of interest.



(a) original image



(b) cropped image



(c) image negative

(d) image thinning

Figure 2: A sample image during preprocessing.

3.1.2 Regional and Geometric Features Extraction

A set of regional and geometry based features (Dileep, 2012) are computed. Based on the applied feature selection technique (section 3.1.3), Extent feature is an effective regional feature that represents the normalized area of the skeleton. It is a scalar measurement that specifies the ratio of handwritten word area to area of the word imaginary bounding ellipse as shown in Figure3.

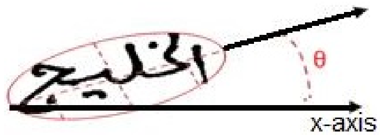


Figure 3: Word Bounding Ellipse.

The geometric features; descriptors of image contours, are computed after dividing image into six different zones (Dileep, 2012). Zoning considers the position of line segments as a feature and satisfy the concept of feature localization. Eight features are computed per zone. First four are the normalized number $\hat{N}$ of horizontal, vertical, left diagonal, right diagonal lines, as defined in equation 1.

$$\hat{N} = 1 - \frac{2N}{10} \tag{1}$$

The second four features are the normalized length $\hat{L}$ of all line types as defined in equation 2.

$$\hat{L} = \frac{L}{A_z} \tag{2}$$

where A_z is the zone area. Line types are determined using the concavity features (Theodoridis and Koutroumbas, 2006) as shown in Figure 4.

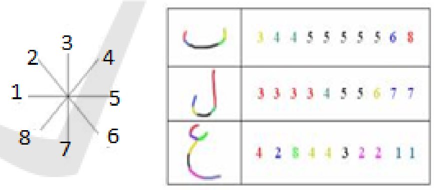


Figure 4: Concavity features.

3.1.3 Random Forest for Feature Selection and Decision Trees Construction

Random Forest classifier perform feature selection to choose most effective features from the computed set of regional and geometric features. A forest of decision trees are then constructed to vote for a group of similar classes corresponding to each test image.

Database classes are split into two branches at each tree node. Splitting is based on features' importance. Importance of features is estimated from their impact on model accuracy. The measured importance of the computed features is shown in Figure 5. The x-axis is the feature, values from 1 till 5 are the computed regional features including number of PAWs,

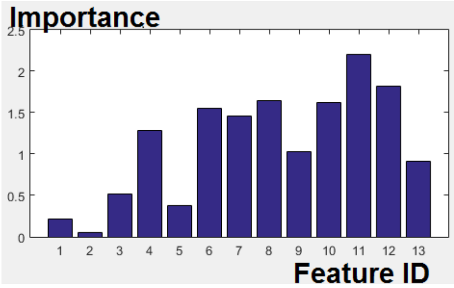


Figure 5: Feature Importance.

number of holes, eccentricity, extent and orientation respectively , other values are the computed set of geometric features (Dileep, 2012). It is clearly shown from Figure 5 that extent;feature 4, is the most relevant regional features, while the whole set of geometric features are all important and affect performance positively.

Finally, based on the measured features importance, the selected set of features includes extent and the 8 geometric features. Based on the selected features, Apriori pruning algorithm (Rokach and Maimon, 2014) match each test sample with a set of similar database classes; called item-sets.

It is a challenging aspect to mine item-sets from large database (Han et al., 2011). If a long item-set is frequent, then all its subsets are frequent as well. For example, a k-item-set (i.e. of length k items) contains total number of frequent item-sets defined by

$$\binom{k}{1} + \binom{k}{2} + \cdots + \binom{k}{k} = 2^k - 1 \quad (3)$$

Each matching set include similar classes with similar features. Different sets may include common classes. Some smaller sets may be a subset of other bigger sets which serve the matching process to be implemented as a binary search tree. The test image is now matched with a set of similar database classes and both are ready for ranking stage.

3.2 Stage 2: Ranking Stage (PHoG & KL-divergence)

Each test image and its matching set of similar classes pass through stage 2. Kullback-Leibler divergence (Ghanim et al., 2018) is computed between Pyramid Histogram of Gradient features of input images (Saïdani and Echi, 2014). Accordingly, the matching classes are ranked from the nearest to the furthest (Ghanim et al., 2018) relative to test image. The objective of this stage is to pass only subset of highly ranked classes to classification stage as presented in Figure 1.

3.2.1 Statistical Features Extraction: Pyramid Histogram of Gradients PHoG

Histogram of oriented gradients HoGs is a statistical-type descriptor that performs orientation analysis at different levels (Ghanim et al., 2018). It captures fine details and more discriminating information about words skeletons than the ordinary HoGs (Saïdani and Echi, 2014).

Oriented gradients are extracted per image zone as shown in Figure 6 by Canny edge detector (Gonzalez and Woods, 2007) as defined in equation 4.

$$\theta = \arctan \frac{G_y}{G_x} \quad (4)$$

Gx and Gy are gradients in x and y direction, θ is orientation [0,360°] which are discretized to eight values (Saidani et al., 2015). PHoG features are computed and normalized per image zone for the 8 defined angular bins. KL-divergence is computed between feature vectors of test image and its matching classes 3.2.2.

3.2.2 Divergence Measure: Kullback-Leibler (KL)

KL divergence measure has been popularly used in data-mining (Ghanim et al., 2018). It is a non-symmetric measure of difference between any two probability distributions; as PHoGs, for orientation analysis. It is a non-symmetric metric measure. The measure from one distribution $q(x)$ to another $p(x)$ is not equal to the measure from $q(x)$ to $p(x)$. It is a non-negative value that equals to zero if and only if $p(x) = q(x)$.

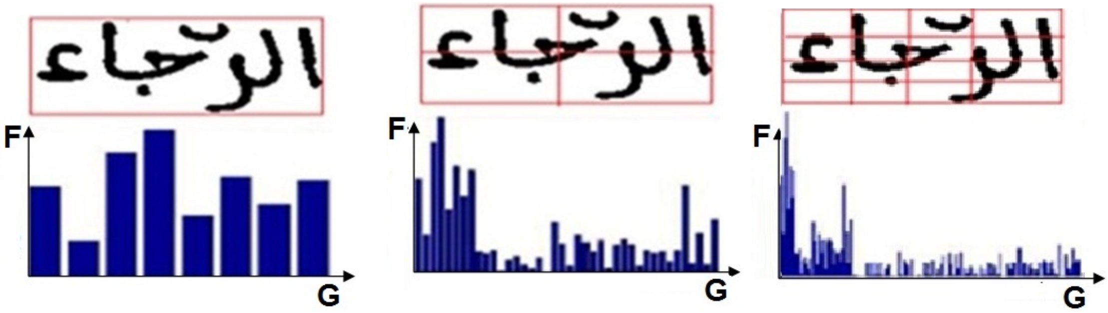
This measurement ranks the members of matching set from the nearest to the furthest relative to the test image. Classes of high ranks pass to final classifying stage instead of passing all database.

3.3 Stage 3: Classification Stage

Finally each test image pass through classification stage with only highly ranked best nearest neighbors classes to vote for final membership class.

3.3.1 Final Feature Vector: Statistical & Geometric Features Extraction

Final feature vector is a combination of the selected features from stage 1 and the PHoG features from stage 2. Final features vector is used to classify the test image as described next section 3.3.2.



(a) Level=1 (b) Level=2 (c) Level=3

Figure 6: Pyramid histogram of gradients (F:frequency, G:oriented gradient).(Ghanim et al., 2018)

3.3.2 Classification: Multi-class Support Vector Machines

A bigger feature vector is now ready to train a multi-class SVM. Only the highly ranked best matching reference classes are used in training SVM. The output finally determines the test image membership training class.

Many surveys (Kumar and Rao, 2013) demonstrated effectiveness of SVM. There are two schemes to convert SVM to series of binary SVM's (Abdiansah and Wardoyo, 2015), one-versus-rest and one-versus-one. In the proposed solution, the one-versus-one approach is applied. It is symmetric SVM model and does not suffer from the unbalanced classification problem.

4 EXPERIMENTS

4.1 Database

The approach is tested on IFN/ENIT database (Pechwitz et al., 2002) of 937 distinct classes. Data-set is composed of 5 parts named a, b, c, d and e.

4.2 Matching Set Selection

Matching sets vary in sizes. Sensitivity is measured by degree of correct class inclusion in the matching set. Random Forest for decision trees construction enhanced sensitivity to be 93.5% instead of 86.5% in (Ghanim et al., 2018). The weighted average matching set size computed from equation 5 is approximately 172.6 different classes, which is approximately 18% of the whole database number of classes.

$$\bar{x} = \frac{\sum_{i=1}^{n}(x_i * w_i)}{\sum_{i=1}^{n} w_i} \tag{5}$$

$\bar{x}$ is the weighted average, x is the set size and w is the normalized weights of sets. Largest set contains 423 different classes (worst case) which is 44.7% of the 946 total database classes.

Figure 7 shows the effect of the different regional and geometric features and Random forest (RF) on the overall matching error. Figure 7a shows that number of holes, PAWs, eccentricity and word orientation cause 21% misclassification error. Figure 7b shows that Extent feature cause an exponential reduction in misclassification error to be 9%. Including the geometric features to Extent feature reduce error from 9% to 6%, Figure 7c.

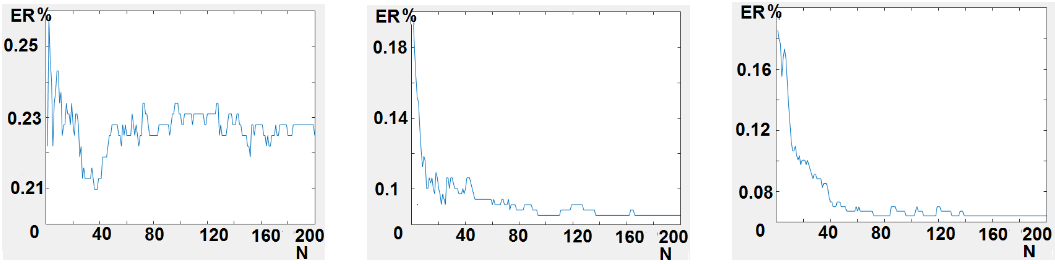
4.3 The Ranking Stage

The approach categorized database into three main parts;labelled 30, 20 and 5, according to average ratio between training and testing samples. Figure 8 shows that increasing PHoG level causes proceeding of correct class in early ranks. This cause fast graph saturation where high recognition rates are achieved. Fastest saturation achieved with label 30 due to existence of enough training samples relative to testing ones. This leads to passing as small sets of classes as possible to final stage and so less training time as shown in Figure 8b and 8c. The correct class rank in worst case is 100 inside matching set. Accordingly, only 10.5% of the total database classes passes to classification stage.

4.4 The Classification Stage

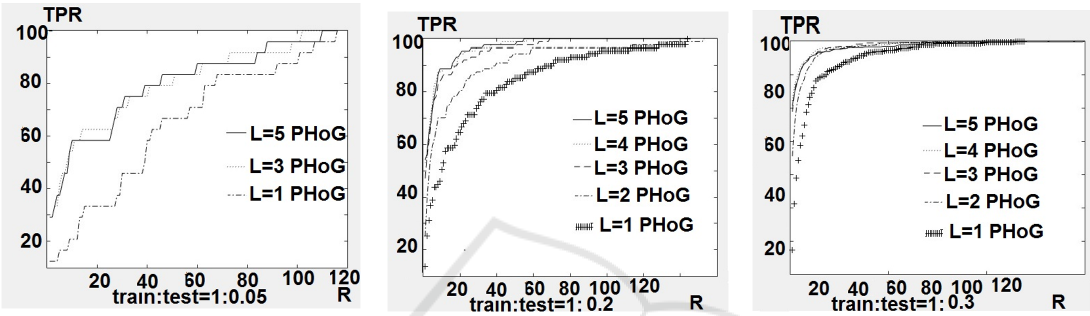
The SVM is applied with different kernel's type at different levels of Pyramid Histogram of gradients as shown in Figure 9.

Final classification is applied on highly ranked classes. The Linear SVM with level 5 PHoG achieves the highest recognition rate. Figure 9a shows SVM output with Level 1 PHoG; original HOG. Figure 9b



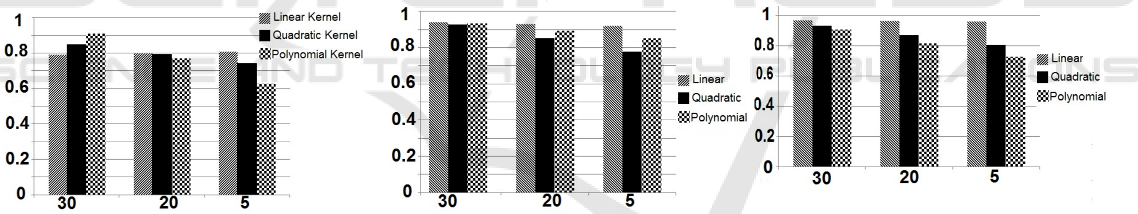
(a) no. of holes, paws and eccentricity and orientation.
(b) Effect of extent after excluding no. of holes, PAWS, ecc, orientation.
(c) Effect of extent and geometric features.

Figure 7: Effect of selected features on Classification Error, (N=number of decision trees), (ER% = error rate).



(a) Experiment on classes with label 30.
(b) Experiment on classes with label 20.
(c) Experiment on classes with label 5.

Figure 8: Effect of Ranking on the Expected Success Rate (Ghanim et al., 2018) (TPR: True positive rate), (R: rank of correct class).



(a) Level 1 PHoG and Geometric features with SVM.
(b) Level 3 PHoG and Geometric features with SVM.
(c) Level 5 PHoG and Geometric features with SVM.

Figure 9: System Recognition Rate.

is for level 3 PHoG. The linear kernel gives the best results with all sets but the polynomial kernel was better than quadratic. Figure 9c displays the system performance on level 5 PHoG. The linear kernel with set labeled "30" outperforms all the other experiments.

4.5 Comparative Experiments and Results

Table 1 represents similar systems' experiments and their results relative to proposed approach. Some classification systems applied word segmentation to character level, while others didn't. Segmentation modify error rates by predicting the correct sequence of word characters based on pre-defined dictionary but increase computation complexity. The proposed approach is applied without segmentation and considered absence of pre-defined dictionary. The results in table 1 indicate the distinction of the proposed solution results than others.

4.6 Reasons of Misclassification

Visual similarity between different classes is one of the main reasons of misclassification as shown in table 2.

Table 1: Comparative results of systems applied on IFN-ENIT.

Approach reference	Training-testing	Approach	Segmentation	Word error rate
(Abandah et al., 2014)	abcd-e	BLSTM-RNN	without	24.28%
(Lawgali et al., 2014)	abcd-e	DCT-NN	with	14.64%
(Jayech et al., 2015)	abc-d	MSHMM	with	8.95%
			without	16.9%
	abcd-e		without	27.6%
			with	17.09%
(Hicham et al., 2016)	abcd-e	denstity-HMM	with	21.05%
(Elleuch et al., 2016)	56 classes	Conv-CNN SVM	with	7%
(Al-Dmour and Abuhelaleh, 2016)	18 classes	Surf-SVM	without	15%
Proposed approach	abc-d	RF-PHOG-KL-SVM	Without	3.6%
	abcd-e		Without	14.6%

Table 2: Sample of visual similarity between classes.

Class name	Similar Class name
الجم	أجيم
السواني	السواسي
بوغراره	بوعراده

(a) Misclassification due to bad handwriting styles

(b) Misclassification due to inaccurate thinning results

Figure 10: Samples of Misclassified Images.

Bad handwriting styles and inaccurate thinning also mislead the system as shown in Figure 10a and 10b. Misclassification is sometimes due to lack of training samples of some classes.

5 CONCLUSIONS

The proposed approach is a cascaded classifier for offline Arabic handwritten recognition. It is applied on IFN/ENIT database. Random Forest improved performance of decision trees. High levels of PHoG increase effectiveness of ranking stage.

6 FUTURE WORK

Future plan is to apply deep learning techniques to improve classification rates and matching process to build more robust recognition systems.

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