Arabic/Farsi Handwritten Digit Recognition using Histogram of Oriented Gradient and Chain Code Histogram

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Abstract: *The aim of this paper is to propose a novel technique for Arabic/Farsi handwritten digit recognition. We constructed an invariant and efficient feature set by combination of four directional Chain Code Histogram (CCH) and Histogram of Oriented Gradient (HOG). To achieve higher recognition rate, we extracted local features at two levels with grids 2×2, 1×1 and it causes a partial overlapping of zones. Our proposed feature set has 164 dimensions. For classification phase, Support Vector Machine (SVM) with radial basis function kernel was used. The system was evaluated on HODA handwritten digit dataset which consist of 60000 and 20000 training and test samples, respectively. The experimental results represent 99.31% classification rate. Further, 5-fold cross validation was applied on whole 80000 samples and 99.58% accuracy was obtained.*

Keywords: *Arabic/Farsi handwritten digit recognition, CCH, HOG, SVM.*

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1. Introduction

Handwritten digit recognition has been one of the most noticeable subject in computer vision for more than some decades. Digit recognition is a subfield of Optical Character Recognition (OCR) which means automatic conversion of scanned images of handwritten or printed text into computer-readable text. Recognizing handwritten digits is a complicated task because of diversity of writing styles caused by varying subject, different type of writing tool and varying level of cares. OCR has many real world applications such as reading passport documents, bank cheque processing, postal mail sorting and automatic license-plate recognition [1, 3, 8, 19, 29, 37, 38].

Due to growing automated systems which take Farsi/Arabic documents as input, there is a high demand for machines that understand Farsi materials. Several researches have been proposed for handwritten Latin digit recognition and obtained reasonable result in term of accuracy [15, 18, 20, 21, 22, 27, 28, 33, 35, 40, 43]. In comparison with Latin script, the number of research in Arabic/Farsi handwritten recognition has been limited.

Arabic and Farsi are the main language of some Middle East countries. Farsi is native language in Iran, Tajikistan and Afghanistan and Arabic-speaking people in Saudi Arabia, Yemen, Iraq and Oman speak and write Arabic. Farsi is spoken by more than 110 million people [27]. Similar to Latin script, handwritten Farsi/Arabic digits have large variations in writing forms, scales and orientations [27].

Like Latin scripts, there are 10 numerals in Arabic/Farsi digits which are written from left to right.

Farsi and Arabic digits are nearly similar but there are some considerable differences related to numerals of 4 and 6 which are written in different forms. Generally, in Farsi, there are two writing styles for the digits 0, 2, 3, 4, 5, 6. Both of these two forms are legal and shown in Figure 1. These style variations make the recognition of Arabic/Farsi numerals more complicated than other languages.

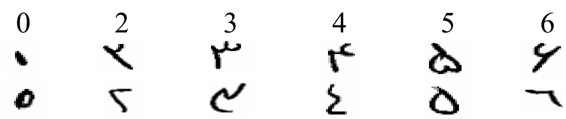
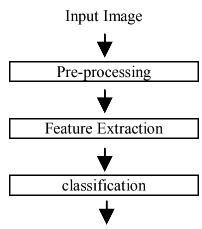


Figure 1. Both legal shapes of some digits in Farsi.

A typical OCR system consists of three parts: Pre-processing, feature extraction and classification. Figure 2 presents a general scheme of an OCR system. Pre-processing is a sequence of operation performed on the input image to improve image quality for further processing and feature extraction. Noise removal, image size normalization, morphological operation and skew correction are some typical pre-processing [10, 14].



Class Label

Figure 2. Recognition system of handwritten digits.

Feature extraction is the most remarkable part of a recognition system that has significant impact on the recognition performance. To compensate the intra-class variation, the extracted feature should be invariant with respect to shape transformation such as translation, scale and rotation. There are a lot of research which use different type of feature like geometric moment, Zernike moment, outer profile and crossing counts [4, 36, 41].

For classification, there are several learning machine algorithms that are used by researchers. Multilayer neural networks [12], Support Vector Machines (SVM) [39], nearest neighbour and search trees are some usual classifier. The SVMs have been developed as a robust tool for classification and regression in noisy and complex domains [23]. Our approaches for each of these three steps have been described in details later.

2. A Literature Review On Arabic/Farsi Handwritten Digit Recognition

In the past decades, several methods for recognizing handwritten digits has been proposed [2, 7, 11, 24, 25, 26, 30, 31, 34, 36, 44]. Here, we mentioned some of them which focused on Farsi/Arabic scripts.

Soltanzadeh and Rahmati [36] used outer profiles, crossing counts and projection histograms from multiple orientations as features. They evaluated their system on their own dataset with 8918 samples and achieved 99.57% accuracy.

Sadri *et al.* [31] proposed new approach of feature extraction. Each digit was considered from four different views and then from each view 16 features were extracted and finally a vector with 64 dimension was passed to SVM. Their experimental carried out on 10425 samples and they obtained 94.14% classification rate.

Mowlaei and Faez [23] suggested the haar wavelet to obtain the features and these features were then fed to SVM for training.

Ziaratban *et al.* [44] proposed a template based feature extraction method. Twenty templates that are believed to be able to capture the most major information from numerals are selected heuristically. Feature extraction is accomplished via template matching: For each template, find the best match in an input image and record the location and the match score of the best match as features. These features are then fed into a multi-layer perceptron for training.

Recently, Salimi and Giveki [32] suggested a new approach to recognize digits by Singular Value Decomposition (SVD) classifier. The decisions obtained by SVD classifiers were combined by a novel proposed combination rule which they named reliable multi-phase particle swarm optimization that never falls in local minima.

From the literature review of some existing works on Farsi/Arabic digits recognition, it is apparent that not much effort was expanded to detect a more efficient feature set (most of them are time consuming and some of them cannot preserve the shape of the input image for feature extraction step). To overcome such problem, we proposed to find out a more effective feature set by combination of hierarchical Chain Code Histogram (CCH) and Histogram of Oriented Gradient (HOG). We extracted CCH from 3 level of spatial domain. Then, HOG was calculated from each 8×8 cell of input image. This combination of feature set, which represent the physical shape of input image and extracted local information of the input image in each level, provided very high accuracy in experimental results.

The remaining part of this paper is organized as follows: Section 3 describes our pre-processing operation. Section 4 explains the feature extraction. Section 5 presents the used classification strategy and section 6 illustrates experimental results.

3. Pre-Processing

In the pre-processing step, some operations are done on image to enhance their quality for next step. All the images in used dataset are clean, so they don't need noise removal technique. However, if the real world data are contaminated with noise, a noise removal approach is needed. The images in used dataset are in different size. Therefore, for simplicity of the feature extraction and classification, we normalized the size of images to 32×32 pixels. In this study, moment based size normalization technique was used which is introduced in [17].

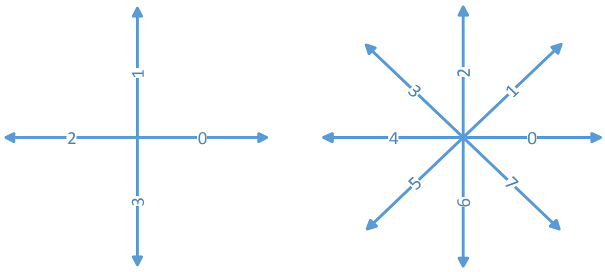
4. Feature Extraction

An ideal feature extractor would produce a representation that makes the job of the classifier trivial. This is achieved by measuring features whose values are nearly similar for objects in same category but are very different for objects in different categories [9].

We employed a combination of CCH and HOG as feature vector in proposed system. Next sections describes CCH and HOG clearly.

4.1. Chain Code Histogram

CCH is one of the most popular feature extraction techniques in recognition task and calculated from the chain code presentation of an object's contour. The Freeman chain code is a compressed way to represent a contour of an object. The chain code is an ordered sequence of n links $\{c_i, i= 1, 2, ..., n\}$ where c_i is a vector linking neighbour pixels. The direction of each vector c_i is encoded with an integer value k= 0, 1, ..., k-1. The common value for K might be four and eight that are shown in Figure 3.



a) Four direction of chain code. b) Eight direction of chain code.

Figure 3. Two presentation of chain code.

The Freeman chain code is sensitive to the starting point. Computing histogram is one solution to compensate this drawback. CCH is a shape descriptor which calculates from chain code sequence. The calculation of the CCH is fast and simple. Equation 1 shows how it is calculated.

$$p_k = \frac{n_k}{n} \tag{1}$$

Where n_k is total number of chain code in direction k and P_k is the normalized value of n_k. In fact, CCH is a normalized histogram of chain code.

It was shown that an appropriate fusion of global and local features will compensate their shortcomings, and therefore improve the overall effectiveness and efficiency [27]. Thus, we suggested using local block-based CCH in two spatial zone with partial overlapping as shown in Figure 4.

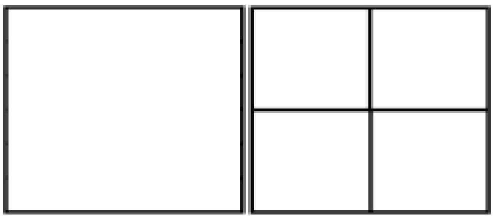


Figure 4. Two level scheme for feature extraction.

At the top level, a four dimensional CCH vector was extracted from whole character image. At the second level, we divided 32×32 original image to 4 blocks and extracted CCH from each block separately. Therefore, we totally obtained a twenty dimensional CCH vector.

The complete steps for extracting 4-CCH features from each block are described below:

1. Discover the contour representation of the block.
2. For each contour pixel, compute the directional information by considering the 8-directions.
3. Compute the histogram from 8-directional chain code sequence.
4. Assuming direction 1 and 5, 2 and 6, 3 and 7 and 4 and 8 as same, so we get 4-directional CCH feature vector for each block.

4.2. Histogram of Oriented Gradient

HOG feature descriptor [6] is one of successful features for object detection and recognition. The key idea behind the HOG descriptors is that local object appearance and shape within an image can be characterized by the distribution of local gradients magnitude and orientation. The HOG descriptor can be computed by splitting the original image into smaller connected zones, called cells and for each cell collecting a 1-D histogram of edge orientations or gradient directions for the pixels inside the cell. The combination of these histograms represents the descriptor.

For improving accuracy, the local histograms can be contrast-normalized by calculating a measure of the intensity across a larger region of the image, called a block and then using this value to normalize all cells within the block. This normalization results is more invariant to changes in illumination or shadowing. In this study, we set the cell size to 8×8 and extracted 9 dimensional HOG from each cell.

5. Classification

SVMs [42] are one of the successful supervised learning methods that is widely used for regression and classification problem. SVMs are based on the margin-maximization principle i.e., SVMs look for a hyper plane that has maximum space from the nearest samples from both categories of this separator. The decision boundary to separate the classes is defined by a subset of training samples which are named support vectors. Support vectors are those of samples that are closest to the separating hyper plane. A linear SVM is shown in Figure 5.

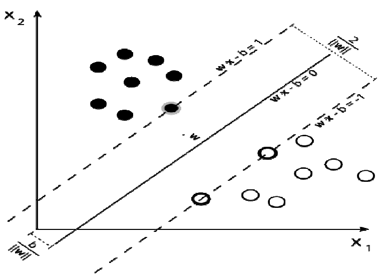


Figure 5. Maximum-margin hyper plane and margins for an SVM trained with samples from two classes.

Given a training set of input-output pairs S={($\vec{x}_i$, y_i) | ($\vec{x}_i$, y_i)™ R^m×R, i= 1, 2, ..., l} where label y_i{-1, 1}, (i= 1, 2, ..., l), the solution of the following optimization problem guarantees the restriction of maximization marginal space:

$$\begin{aligned} &min: P(\vec{w}, b, \vec{\xi}) = \frac{1}{2}\vec{w}^T\vec{w} + C\sum_{i=1}^{l}\xi_i \\ &subject\ to: \begin{cases} y_i(\vec{w}^T\varphi(\vec{x}_i)+b) \geq 1-\xi_i \\ \xi_i \geq 0,\ i=1, 2, ..., l \end{cases} \end{aligned} \tag{2}$$

Where $\vec{w}$ is m-dimensional vector, b is a scalar and ξ is the slack variables. $C \geq 0$ is the penalty parameter controlling the trade-off between the maximization of the margin and the minimization of the classification errors.

The function ϕ is the kernel function and maps each training samples x_i into a higher dimensional space. SVMs find a linear separating hyper plane with the maximal margin in new space as shown in Figure 6.

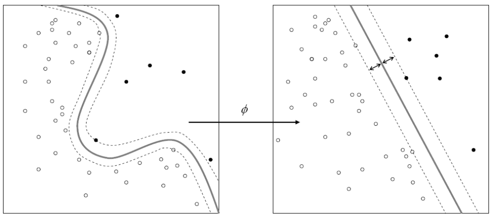


Figure 6. Kernel function maps linear inseparable samples to a higher dimensional space and separate them by a hyper plane in new space.

To find the solution of the primal optimization problem, it is usually done by solving its dual problem of Lagrangian formulation:

$$min: D(\vec{\alpha}) = -\sum_{i=1}^{l} \alpha_i + \frac{1}{2} \sum_{i=1}^{l} \sum_{j=1}^{l} y_i y_j \alpha_i \alpha_j K(\vec{x}_i, \vec{x}_j)$$

$$subject\ to: \begin{cases} \sum_{i=1}^{l} y_i \alpha_i = 0 \\ 0 \leq \alpha_i \leq C, \quad i = 1, 2, ..., l \end{cases} \tag{3}$$

Where $a_i(i= 1, 2, ..., l)$ is a positive Lagrange multiplier. Furthermore, $K(x_i, x_j)=\phi(x_i)^T\phi(x_j)$ is called the kernel function. The following three basic kernels are used commonly:

$$Linear: K(x_i, x_j) = x_i^t x_j$$

$$Polynomial: K(x_i, x_j) = (\gamma x_i^T x_j + r)^d \gamma > 0$$

$$Radial\ Basis: K(x_i, x_i) = exp(-\gamma \|x_i - x_i\|^2) \gamma > 0$$

Where y, r and d are kernel parameters, in this paper, we experimented linear, Gaussian and polynomial kernels and we obtained the greatest result using Gaussian kernel or radial basis function.

The decision function is defined as:

$$g(\vec{x}) = sign\{\sum_{\vec{x}_i \in SVs} \alpha_i y_j K(\vec{x}_i, \vec{x}_j) + b\} \tag{4}$$

Where vector $\vec{x}_i$ is one of the Support Vectors (SVs) when $0 \leq a_i \leq C$ SVMs is naturally a binary classifier and it is not straightforward to use SVMs in multiple-class classification problem. One-against-one and one-against all, are two different techniques that can be applied to develop binary support vector classifier for multi-class problems. Hsu and Lin [13] compared these two approaches on different datasets and concluded that the first approach is more appropriate in practice. We used LIBSVM [5] to build SVMs in our experiments. LIBSVM is an efficient open source library tool for classification and regression problems.

The one-against-one method is implemented for the multi-class SVMs in LIBSVM. For N class problem, one-against-one design a SVM classifier for each pair of classes. Therefore, we have totally $\frac{N(N-1)}{2}$ classifier. Here, classification is done by a max-wins voting strategy, in which every classifier assigns the instance to one of the two classes, then the vote for the assigned class is increased by one vote and finally the class with the most votes determines the instance classification.

6. Experimental Result

To train a learning machine successfully, a wide-ranging dataset is needed. Most of the researchers in Arabic/Farsi handwritten recognition, have used their own dataset to train and evaluate their systems [44].

In this paper, all the experiments have been carried out using the standard HODA Farsi/Arabic handwritten digits dataset provided by Khosravi and Kabir [16]. This dataset contains 60,000 training samples and 20,000 test samples. This dataset is the largest dataset related to Farsi/Arabic handwritten numerals. All samples are in the form of binary image. An instance of each digit and different styles is shown in Figure 7.

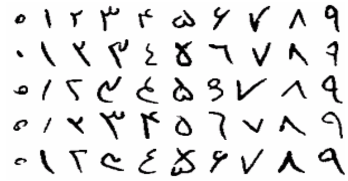


Figure 7. Different styles of handwritten Arabic/Farsi digits [16].

The proposed system was implemented by MATLAB version 8.1 (Release 2013a) 64bits. We used an Intel Core i7-3610QM processor (4M cache, 2.30GHz) with 8GB of RAM memory.

The accuracy of SVM model is highly dependent on the selection of the model parameters. Finding the optimal parameters is called the model selection process. Grid search algorithm is a straightforward technique for selecting appropriate model. It trains SVMs with all chosen pairs of parameters and monitors them in accordance with the training accuracy. Finally, the parameters related to the best result are used to train the model.

As suggested in LIBSVM guide, we set the range of each parameter for grid searching as y™$[2^{-11}, 2^{-9}, ..., 2^1, 2^3]$, C™$[2^{-5}, 2^{-3}, ..., 2^3, 2^5]$. Also, to avoid overfitting, a 5-fold cross validation was applied. The SVMs were trained with all 8×6=48 different combinations and the greatest validation rate was achieved by $y=2^{-7}$, $C= 2^3$.

Using 60000 training sample, we evaluated SVM classifier on 20,000 test samples and 99.31% accuracy was obtained. In another trial, we combined all train and test samples and applied 5-fold cross validation on whole 80,000 samples. In 5-fold cross validation, all existing samples are randomly divided into 5 equal size parts. One of the five parts is taken as the validation data for testing the classifier and the remaining are used for training. The cross validation method is then repeated 5 times. To yield a single estimation, the average of all five iterations result is calculated.

The advantage of the cross validation is that all samples are used for both training and validation and each sample is used for validation exactly once. In cross validation process, we obtained 99.58% classification rate.

Figure 8 shows the confusion matrix for 10 numerals. The results illustrate the effectiveness of the proposed feature extraction technique.

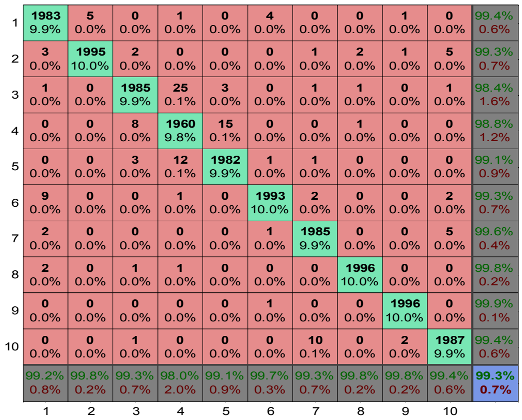


Figure 8. Confusion matrix of the results.

It is apparent from Figure 8 that there are some digits more frequently misclassified. It can be seen from the confusion matrix that the major misperceptions were amongst 2, 3 and 4. This is caused by the fact that they are fairly similar in shape.

Some digit images were misclassified by the proposed model are shown Figure 9. The left label is the true label and the right label is the incorrect predicted label.

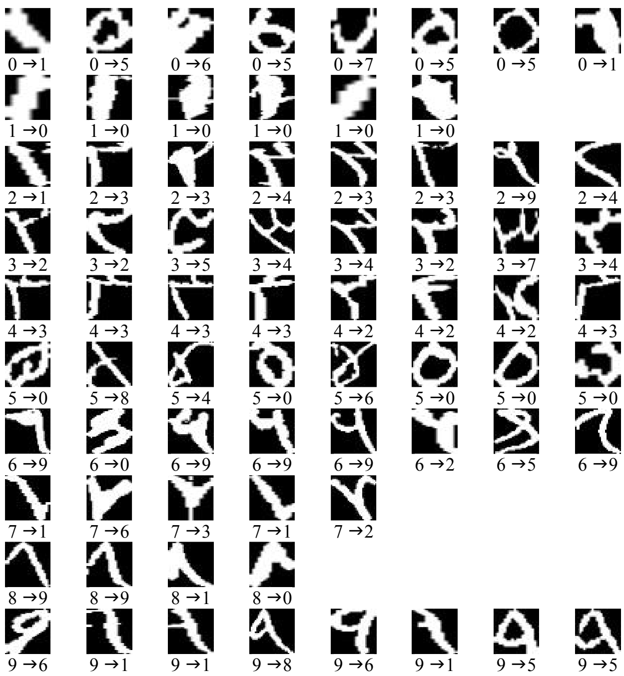


Figure 9. Some misclassified samples.

Figure 10 represent classification rate for each digit in a more clear way.

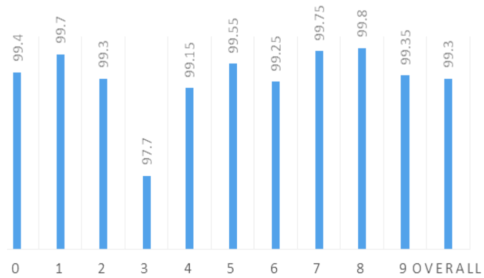


Figure 10. Recognition Accuracy for each digits.

To evaluate our proposed scheme, we compared the performance of proposed method with some recent works that are proposed for Arabic/Farsi numeral recognition. The results are demonstrated in Table 1. It should be noted that most of the existing works were evaluated on smaller datasets. Meanwhile, we used 80,000 data for our experiments.

Table 1. Comparison.

Algorithm	Data size		Accuracy	
	Train	Test	Train	Test
Shirali-shahreza	2600	1300	--	97.80
Soltanzadeh.and Rahmati [36]	4979	3939	--	99.57
Dehghan. and Faze [7]	6000	4000	--	97.01
Harifi. and Aghagolzadeh [11]	230	500	--	97.60
Ziaratban *et al.* [44]	6000	4000	100	97.65
Mowlaei, Faez	2240	1600	100	92.44
Mowlaei	2240	1600	99.29	91.88
Mozaffari	2240	1600	98.00	91.37
Mozaffari	2240	1600	100	94.44
Sadri *et al.* [31]	7390	3035	--	94.14
Salimi and Giveki [32]	6000	2000	100	97.02
Rashnodi *et al.* [30]	60000	20000	100	98.84
Alaei *et al.* [2]	60000	20000	99.99	98.71
Rashnodi *et al.* [30]	60000	20000	100	98.84
ProposedAlgoritm	60000	20000	99.98	99.31
ProposedAlgo.(5 fold)	80000		99.58	

The highest dataset of size 10, 000 was used by a recent work due to Ziaratban *et al.* [44], where as we used 80, 000 data for our experiment. The highest accuracy was obtained from the work due to Soltanzadeh and Rahmati [36] but they have experimented on their own dataset with only 8,918 samples and used 257 dimensional features.

We considered 80, 000 data for our system and we obtained 99.31% accuracy using only a 164 dimensional feature vector. As the comparison shows, our system has the highest accuracy among other works which uses HODA standard dataset.

7. Conclusions

In this paper, we proposed an efficient feature set for Arabic/Farsi handwritten digits recognition. Experimental result indicates that this feature set is highly discriminative. We combined global and local block-based CCH vector with HOG features. For classification, we fed the feature set to One-Against-One SVMs with Gaussian kernel. The parameter of SVM was trained by grid search methodology. 99.31%

accuracy with 60,000 training sample and 20,000 test samples was obtained. Furthermore, we achieved 99.58% accuracy with cross validations method. It should be mentioned that most of misclassifications belongs to class 2, 3 that are hard to recognize even by human beings.

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