

# CLASSIFIER FUSION METHOD TO RECOGNIZE HANDWRITTEN PERSIAN NUMERALS

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## ABSTRACT

*Recognition of Persian handwritten characters has been considered as a significant field of research for the last few years under pattern analysing technique. In this paper, a new approach for robust handwritten Persian numerals recognition using strong feature set and a classifier fusion method is scrutinized to increase the recognition percentage. For implementing the classifier fusion technique, we have considered  $k$  nearest neighbour (KNN), linear classifier (LC) and support vector machine (SVM) classifiers. The innovation of this tactic is to attain better precision with few features using classifier fusion method. For evaluation of the proposed method we considered a Persian numerals database with 20,000 handwritten samples. Spending 15,000 samples for training stage, we verified our technique on other 5,000 samples, and the correct recognition ratio achieved approximately 99.90%. Additional, we got 99.97% exactness using four-fold cross validation procedure on 20,000 databases.*

## KEYWORDS

*Persian handwritten recognition,  $k$  nearest neighbor, linear classifier, SVM classifier, classifier fusion.*

## 1. INTRODUCTION

Nowadays handwritten characters recognition is one of the most popular research areas, because it has various application potentials. Bank cheques processing, Postal Automation, Automatic data entry, etc. are some of its potential application are. Most of the handwritten character recognition methods for, Arabic, English, and Chinese scripts are reviewed in [1-3]. As regards there is no popular method for Persian handwritten character recognition due to cursive-ness of Persian handwritten, and various way of characters combination together and also, characters position in words. By the following passages, we studied edge maps, transit and directional frequencies effect in the numeral image contour pixels as features, which kept morphological information of input and then applied fusion of classifiers as classifier.

In Iran and some of its neighbouring countries, the Persian numerals have usage. Also, the Persian has 10 numerals. Alphabets of Persian and Arabic scripts are written from right to left but in their text, digits are taken place from left to right. Despite the similarity of Persian and Arabic numerals, there are a few important differences between their scripts [4]. Normally, in Persian

there are two types of writing for the digits 0, 2, 4, 5 and 6. These characteristics make Persian numerals recognition so sophisticated than other languages [4]. Fig. 1 shows the Examples of Persian printed and handwritten digits.

0	1	2	3	4	5	6	7	8	9

Figure 1. Sample of Persian Handwritten numerals [4]

In the related works pertinent to the Persian handwritten character recognition, many approaches for feature extraction and classification has been proposed. Some of the latest methods in field of feature extraction are; shadow and segmentation codes [5-7], fractal approach [8], profiles [9], moment features [10], template matching [11], structural feature set [12] and wavelet [13], [14]. Also for classification stage different types of Neural Networks [5-8], [10], [11], SVM's [9], [13], [15], Nearest Neighbour [12], multiple classifier [16], [17] have been implemented. What achieved from the literature survey on Persian handwritten character recognition, it is clear that not much attempt was increased to recognize a more capable feature set (some of them are time consuming and some of them cannot keep the structure of the input image for feature extraction stage), which could more suitably be respond to the recognition part [4]. For solving this kind of issue, we investigated more robust features with use of transit, edge maps and modified contour chain code of every window-map, and then apply fusion of classifiers for classification. This kind of feature set, which explicit the somatic shape of input character and take out local information of the input image in each window-map, provided very good correctness in experimental stage.

We ought to remark that the suggested system did not use any pre-processing methods (skew and tilt detection/improvement, smooth out, noise elimination, etc.) that were luxurious processes. Likewise, strength of our feature set was under treatment some of these issues such as skew and slant reasonably.

The rest of our paper is organized as follows: feature extraction technique is detailed in Section two, classification stage is described in Section three, experimental results and comparative investigation are labelled in Section four and finally in last section we assign the conclusion.

## 2. FEATURE EXTRACTION TECHNIQUE

In this phase we will extract chain-code, modified edge maps and transition feature set. Extracting tactic of these feature set are detailed in the next subsections.

### 2.1. Directional Chain Code Frequencies Feature Set

Directional chain code frequencies of the outline points of the input image are very useful for different application such as character segmentation, recognition, etc. [18]. In our proposed method as a first feature set we extracted chain-code directional frequencies of outline pixels of the images by the following rule: First the minimum rectangle covering the handwritten character (bounding box) is extracted for every input image, Then for removing the features to size and

position, we adapted each image to a normal size of 49×49 pixels. We selected this normalized value based of many experimentations and a geometric study. Fig. 2(a) shows the normalized image with its covering rectangle and in Fig. 2(b) the extracted outline points of the character is shown.

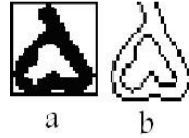


Figure 2. (a): bordering of a normalized image (b): Digit ‘5’ outlineshape

By possession a window-map of size 7×7 on the image, we scanned the image outline horizontally from the top left maximum point to flat maximum point (that contains 49 no overlapped blocks) and we extracted a 8 directions chain code frequencies for each block (8 directions were depicted in Fig. 3(a)). As a replacement extracting the feature set in terms of 8 orders, we have offered to simplify the features into 4 sets fit to 4 orders (Fig. 3(b) shows the four directions), that the horizontal direction code are determined by the 0 and 4 directions, vertical direction code are showed by the direction 2 and 6, also the principal diagonal direction are determined by the direction 1 and 5 and finally the off diagonal direction code is masked by the 3 and 7 directions. Therefore, in every block, we acquired four values signifying the occurrences of these four orders and these quantities were used as local contour direction feature set. For extracting these features, an unvarying block with 49 (7×7) size is considered in every image and we calculated four features (four directions) in each block so we acquired 49×4=196 features for every image.

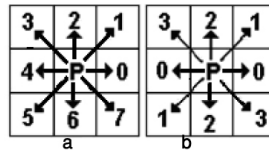


Figure 3. (a): chain code pattern for 8 direction (b): chain code pattern for 4 direction

## 2.2. Modified Edge Maps Features

In this stage, at the beginning, an N x M image is converted into the thinning form and then reshaped into a 49 × 49 matrix. For extracting the four distinct edge maps (horizontal, vertical and two diagonals (45° and -45°)) the Sobel operators was used. After that these four distinct edge maps are distributed into 49 sub-images of 7 × 7 pixels. Then the feature set are gotten computing the proportion of black pixels in each sub-image (a feature set with 49 dimension for each image). Finally these features are joint to form a single feature vector holding 196 (49 x 4) features.

## 2.3. Transition features

The third feature set that investigated in this paper is based on the extracting the transition value from background to foreground pixels in both vertical and horizontal directions. Our extracting The transition feature set is mostly like a transition feature set that has been proposed by Kumar et al [19]. For extracting transition information, image is skimmed from top to bottom and left to right. Following actions shows the way of these feature extraction.

Action1: Distribute the contoured image of a handwritten image into 49 part with size of 7×7.  
 Action2: Computethe number of transitions for each part and extract the 49 features for each character image.

### 3. CLASSIFICATION BY ENSEMBLE TECHNIQUE

Ensemble technique has wonderful application in different techniques and widely used in pattern classification and machine learning. the diverse kinds of ensemble techniques has been proposed before and among them theclassification fusion method is the most important type of the ensemble classification. In this technique, numerous classifiers are trained on a same feature space and then,the results of these classifiers are mixed to get a more precise classification [20]. In the current paper, we have used K-Nearest Neighbour (KNN), Linear (L) and Support Vector Machine (SVM) classifiers for ensemble technique. The features gained from Directional Chain Code (DCD) are applied to SVM, the Modified Edge Maps (MEM) feature Set is applied to linear classifiers and Transition features are applied to KNN separately. The prediction of these classifiers is combined using majority-voting procedure to appropriately classify the sample.

#### 3.1. Classification with use of the K-Nearest Neighbour

If you faced with the classification problem has pattern classes you can use an efficient technique called the K-nearest neighbor classifier that display a reasonably limited degree of variability. With calculating the distance between the input pattern and the training patterns it could recognize each input pattern with certain accuracy that has given.During the classification only k nearest prototypes could takes into the input pattern.the final decision is performed with use of majority of class voting.In the k-Nearest neighbour technique, the distance among train and test set is computed for determining the class of the test set.In the Equation (1) the applying method is detailed:

$$d = \sqrt{\sum_{k=1}^N (x_k - y_k)^2} \quad (1)$$

In the above equation,  $x_k$  is the collection stored feature value, N shows the entire number of features in feature set and  $y_k$  is the nominee feature value.

#### 3.2. Linear Classifier (LC)

Linear classifier (LC) is a kind of the statistical classifier thatuses a value of the linear mixture of the featuresfor generating a label of class.The application of the linear classifier is mostly on the circumstances where the speed of classification is an important issue.LCfrequentlyeffortexcellently when the number of magnitudes in feature vector is huge. It can be signified as revealed in equation (2):

$$y = f(w, x) = f(\sum_j w_j x_j) \quad (2)$$

Which  $w_j$  is weight vector, learned from a set of marked training examples and the  $x_j$  is the feature vector of testing model and f is a simple function that applies the value to the individual classes based on a confident threshold.

### 3.3. Support Vector Machines (SVM) Classifier

Support vector machines (SVMs) are one of the most important, and powerful in pattern learning and also in pattern recognition, because it support high dimensional data and at the same time, providing good generalization properties. Additionally, in data mining and pattern recognition applications, SVMs have very usages. Considered that  $X = \{(x_i, y_i)\}_{i=1}^n$  are samples of  $n$  training, where,  $y_i \in \{-1, 1\}$  is a class label of sample  $x_i$ , and  $x_i \in R^m$  is an  $m$ -dimensional sample in the input space. with the minimal classification errors, SVM finds the optimal separating hyper plane (OSH). Equation (3) shown the linear separation hyper plane.

$$f(x) = W^T x + b \quad (3)$$

Here  $b$  and  $W$  are the bias, and weight vector. By solving the optimization problem (6), the optimal hyper plane can be obtain, where variable  $C$  controls the effect of the slack variables, and  $\zeta_i$  is slack variable for obtaining a soft margin. Decreasing the value of  $C$  cause to increasing of separation margin. In a SVM, maximizing the generalization ability of the SVM cause to optimal hyper plane obtained. Anyhow, the obtained classifier may not have high generalization ability in a nonlinear separable training data. The original input space should be mapped into a high-dimensional in order to enhancing the linear severability purpose. Now, with using the nonlinear vector function  $\varphi(x) = (\varphi_1(x), \dots, \varphi_l(x))^T$ , witch maps the  $m$ -dimensional input vector  $x$  into the  $l$ -dimensional feature space, the OSH in the feature space is given by equation (4):

$$f(x) = W^T \varphi(x) + b \quad (4)$$

Equation (5) defined a decision function for a test data:

$$D(x) = \text{Sign}(W^T \varphi(x) + b) \quad (5)$$

By solving the following quadratic optimization problem, the optimal hyper plane can be found:

$$\text{Minimize } \frac{1}{2} \|W\|^2 + C \sum_{i=1}^n \zeta_i$$

$$\text{Subject to } y_i (W^T \varphi(x) + b) \geq 1 - \zeta_i$$

$$\zeta_i \geq 0, i = 1, \dots, n \quad (6)$$

As mentioned before, SVMs classifier is introduced for binary problem classification, yet, our proposed method has more than two classes for classifications. For solving this problem, multiclass classification strategies that mentioned in [21] can be used. The greatest common ones are the one-against-one (OAO) and the one-against-all (OAA) approaches [22]. The one-against-one is using the  $(n(n-1))/2$  equation for combinations of all class pairs. What achieved from the experimental results we find out that the one-against-all is more fitting for our proposed method. We used OAA for our character classification.

Our proposed classifier fusion method is sum up in the below algorithm. In addition Fig. 4 shows the recognition way for entrance test image by applying fusion of classifier.

**Algorithm Begin:**

Input: a set of test samples and training samples.

Output: the class label for determining the test sample belongs.

Method: Step1: Extract the directional chain code (DCD), Modified Edge Maps (MEM) and transit (T) features for the training sample and test sample using previously discussed approaches respectively.

Step 2: Apply the DCD, MEM and T features obtained for the training samples to train the SVM, KNN and L classifiers respectively and separately.

Step 3: Apply the DCD, MEM and T features obtained for the test samples to each of the classifier.

Let the prediction of the classifiers be  $p_1$ ,  $p_2$  and  $p_3$

Step 4: Predict the class of the test sample as

Class = Majority of the  $\{p_1, p_2, p_3\}$

**End**

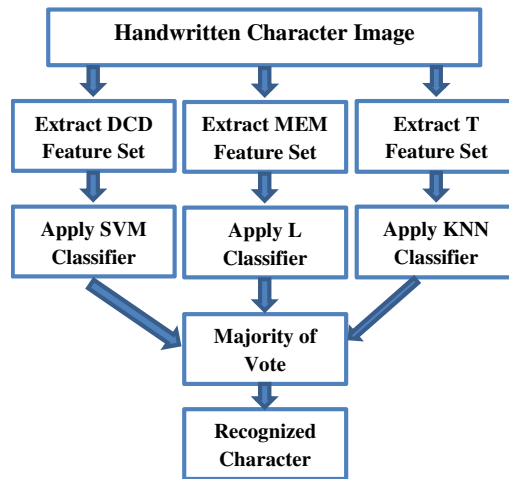


Figure 4. Architecture of the classifier fusion method to recognize handwritten numerals

#### 4. PRACTICAL RESULTS OF THE PROPOSED METHOD

For analysing of the proposed method, a set of the 15,000 samples for training stage and a set of the 5,000 for test stage are considered as indicated in [23]. These samples contain Iranian Postal and National Codes and were extracted with use of the 200 dpi resolution scanner from different registration forms of the Iranian university entrance exam [24]. As we mentioned in section 2 the writing styles of different persons, samples sizes were extremely different, we standardized them to the constant size. By considering the 15,000 samples for the training stage, we evaluated our method on other 5,000 samples and we achieved 99.90% precision. What achieved from the experimental result, we obtained an exactness of 100% when the 20,000 data were utilized as

training stage and the similar dataset was used for testing stage. For further analysing we separated our data set into 4 subclass and testing is estimated on each subclass using reminder of the 3 subsets for training stage. The mean of the recognition rates for all the four test subclass is achieved about 99.97%. Table 1 shows the performance comparison of the proposed method with the state of the art methods.

Table 1. Recognition rates of the diverse approaches for recognizing the Persian handwritten numerals

Method	Database size		Accuracy of the method (%)	
	Train	Test	Train	Test
Azad et al. [4]	15000	5000	-	99.82
Shahreza et al.[5]	2600	1300	-	97.80
Harifi et al. [6]	230	500	-	97.60
Hosseini et al. [7]	480	480	-	92.00
Mozaffari et al. [8]	2240	1600	98	91.37
Rahmati et al.[9]	4979	3939	-	99.57
Dehghan et al. [10]	6000	4000	-	97.01
Faes et al. [11]	6000	4000	100	97.65
Faes et al. [12]	2240	1600	100	94.44
Mowlaei et al. [13]	2240	1600	100	92.44
Mowlaei et al. [14]	2240	1600	99.29	91.88
Sadri et al. [15]	7390	3035	-	94.14
Parvin, et al [16]	40000	2000	-	97.12
Parvin, et al [17]	60000	10000	-	98.89
Our proposed method	15000	50000	100	99.90
Our proposed method With 4 subset	15000	50000	100	99.97

For evaluation of the proposed method we used a dataset with 20,000 samples and we achieved 99.90% and 99.97% precisions using mentioned method. In our achievement with high accuracy (about 99.90%), we detected confusion numerals in the recognition stage among some digits. The main confusions were between 2, 4 and 3. This occurred since 2, 3 and 4 resemble each other. In Fig. 5 the success and confusion rate for each character are depicted.

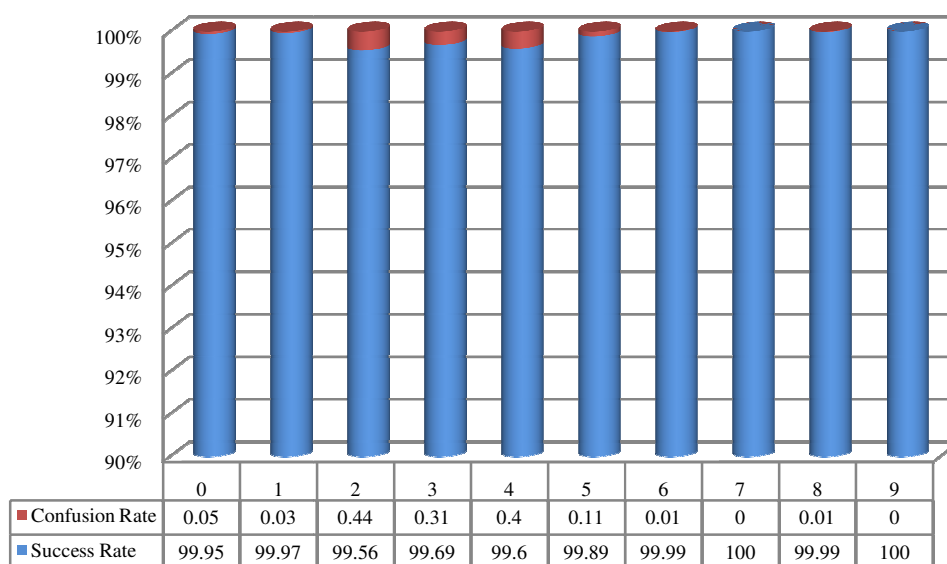


Figure 5. Success and confusion rate of the proposed approach for each Persian numeral

## 5. CONCLUSIONS

In this paper, for robust Persian handwritten numerals recognition we have investigated three feature extraction approaches such as directional chain code, modified edge maps and transit. For obtaining these feature set we transformed each image to the contour shape, then with use of block based method we achieved these three features sets. In the beginning, SVM, Linear and K nearest neighbour classifiers are used for the classification. Further, the recognition accuracy was enhanced with use of classifier synthesis method. What achieved from the experimental results, it could be proved that our proposed technique has good performances on Persian handwritten numeral recognition. In addition, in the result part we detailed the reason of the misclassification. Most of the misclassification samples on our method were from classes of 2, 3 and 4, which have similar structure.

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