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Recognition of Handwritten Persian/Arabic Numerals Based on Robust Feature Set and K-NN Classifier

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Abstract: - Persian handwritten numerals recognition has been a frontier area of research for the last few decades under pattern recognition. Recognition of handwritten numerals is a difficult task owing to various writing styles of individuals. A robust and efficient method for Persian/Arabic handwritten numerals recognition based on K Nearest Neighbors (K-NN) classifier is presented in this paper. The system first prepares a contour form of the handwritten numerals, then the transit, angle and distance features information about the character is extracted and finally K-NN classifier is used to character recognition. Angle, transit and distance features of a character have been computed based on distribution of points on the bitmap image of character. In K-NN method, the Euclidean distance between testing point and reference points is calculated in order to find the k-nearest neighbors. We evaluated our method on 20,000 handwritten samples of Persian numerals. Using 15,000 samples for training, we tested our method on other 5,000 samples and obtained 99.82% correct recognition rate. Further, we obtained 89.90% accuracy using four-fold cross validation technique on 20,000 dataset.

Keywords: Persian/Arabic Numeral Recognition, feature extraction, KNN classifier

1. Introduction

With the increased use of Persian/Arabic writing in many day-to-day businesses in Persian/Arabian countries, it has become necessary for the machines to understand handwritten materials written in Persian/Arabic. As a part of Persian/Arabic scripts, numeral strings and isolated numerals play an enormous role. OCR for handwritten documents in some languages (English, Chinese, Japanese, etc.) has reached to a promising level [1]. The OCR for Persian/Arabic has not grown up like those languages because of the cursive-ness of handwritten in Persian/Arabic and multiple forms of each character with respect to its position in words. Towards this end, we studied the effect of transit, angle and distance in the foreground pixels of numeral image as features, which kept shape information of input and then applied K-NN as classifier.

A. The Persian Numerals Characteristics

Persian numerals are used in Iran and in some of its neighboring countries. Comparable to other

scripts, in Persian also there are 10 numerals. In Persian/Arabic scripts, alphabets are written from right to left but digits are written from left to right. Persian and Arabic numerals are almost the same; but there are some important differences between handwriting of digits of these two scripts [2]. Generally, in Persian digits, there are two types of writing for the digits 0, 2, 4, 5 and 6. These characteristics make the recognition of Persian numerals more complicated than in other languages. Examples of Printed and handwritten Persian digits are shown in Figure 1.

B. Brief Survey on Numeral Recognition

In the literature survey particularly relevant to Persian/Arabic languages, there are many methods for feature extraction and classification. As feature extraction methods; segmentation and

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shadow code [3-5], fractal code [6], profiles [2, 7], moment [8], template [9], structural feature (points, primitives) [10] and wavelet [11, 12] have been used.

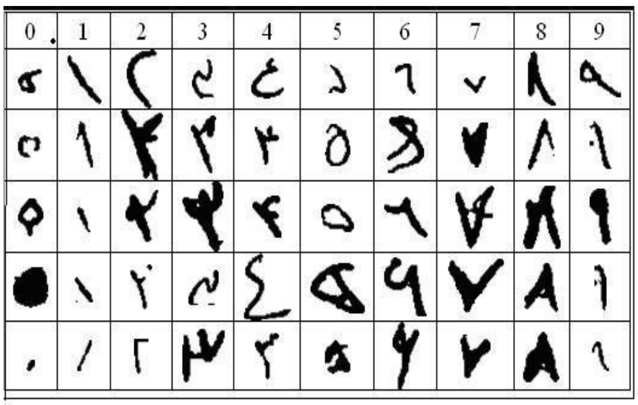

Figure 1: Handwritten Sample of Persian Digits

For classification, different types of Neural Networks [3-6], [8, 9], SVM's [2, 7, 11] and Nearest Neighbour [10] have been applied. From the literature survey of the existing pieces of works on Persian/Arabic numerals recognition, it is evident that not much effort was extended to identify a more efficient feature set (most of them are time consuming process and some of them cannot preserve the shape of the input image for feature extraction step), which could more appropriately be reacted to the recognition phase. To overcome such problem, we proposed to find out a more effective feature set based on transition, distance and angle of each window-map, and then apply KNN for classification. This type of feature set, which expressed the physical shape of input image and extracted local information of the input image in each window-map, provided very good accuracy in experimental part. The robustness of our feature set was taken care of some of issues like skew and slant reasonably. The organization of rest of the paper is as follows: In Section II we illustrate feature extraction and character classification technique, Section III describes experimental results and comparative analysis and finally in last section we present conclusion.

2. Feature Extraction

In our system we computed features based on transit, angel and distance of contour pixels of the images as follows: First we found the bounding box (minimum rectangle containing the numeral) of each input image which is a two-tone image. Then for better result and independency of features to size, font and

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position (invariant to scale and translation), we converted each image (located in bounding box) to a normal size of 60×30 pixels. We chose this normalized value based of various experiments and a statistical study. With a statistical study on behavior of training dataset, we found that more than 96% of the images have a width/length less than 30 pixels. To obtain numeral shapes more clear we normalized them into 60×30. In Figure 2(a), a normalized image with its bounding box is shown. We extracted the contour of the normalized image Figure 2(b).

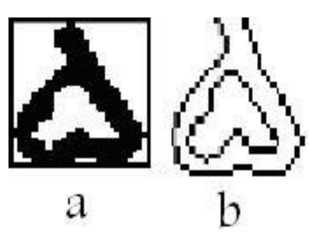

Figure 2: (a): Bounding box of a normalized image (b): Digit '5' in Persian and its contour

We scanned the image contour horizontally by keeping a window-map of size 10×10 on the image from the top left most point to down right most point (18 non overlapped blocks). For each block the transit, angel and distance feature were computed. To extract features, we considered 18 (10*10) uniform blocks in each image and we computed three features in each block so we got 18×3=54 features for each image.

A. Angel Features Extraction

Angle features are very important features in order to achieve higher recognition accuracy and reducing misclassification. These features are extracted from image by the equation (1):

$$(a_b) = \frac{1}{n} + \sum_{k=1}^{n_b} \theta_k^b \quad ,b=1,2,3,... \quad (1)$$

In the top a_b relation, is angel average for any block and θ_k^b angle of white pixel to block horizontal level. The steps that have been used to extract these features are given below:

Step I: Divide the input image into n (n=18) number of block, each of size 10×10 pixels.

Step II: Calculate for each block of image, angel degree with use of equation (1) and set These 18 sub-features as an angel feature.

Step III: Corresponding to the zones whose angel does not have a foreground pixel, the feature value is taken as zero.

Using this algorithm, we will obtain 18 features corresponding to every block.

B. Distance Features Extraction

In this step distance average of whole pixel of block which pixel color is white, are measured with pixel that are in left and bottom coroner of block. With regard to number of block, 18 features of distance mean are extracted for any image. Equation (2) shows this feature extraction:

$$(y_b) = \frac{1}{n} + \sum_{k=1}^{n_b} d_k^b \quad ,b=1,2,3,... \quad (2)$$

In top relation y_b is distance mean for any block and d_k^b is distance of white pixel of agent of any block. Following steps have been implemented for extracting these features.

Step I: Divide the input image into n (n=18) number of block, each of size 10×10 pixels.

Step II: Calculate for each block of image, Euclidean distances from foreground pixel to the agent point of block and set their average as feature.

Step III: Corresponding to the zones whose does not have a foreground pixel, the feature value is taken as zero.

Using this algorithm, we will obtain 18 features corresponding to every block.

C. Transit Feature Extraction

In a binary image, whenever a pixel value changes from 0 to 1 or 1 to 0 it indicates the information about the edge. This information is very significant as it denotes the geometry of the character and helps in identifying the character [13]. In order to capture this information, we have used Run Length Count (RLC) technique. In the proposed method, for every zone, we find the Run Length count in horizontal and vertical direction. A total of 18 features will be extracted for each characters and this will serve as feature vector. Following steps have been implemented for extracting these features.

Step I: Divide the input image into n (n=18) number of block, each of size 10×10 pixels.

Step II: Calculate for each block of image, Run Length count in horizontal and vertical direction and set their ratio as feature.

Step III: Corresponding to the zones whose does not have a foreground pixel, the feature value is taken as zero.

Using this algorithm, we will obtain 18 features corresponding to every block. Figure 3 shows the horizontal run length.

0	1	1	1	0	0
0	0	0	1	1	0
1	1	1	0	0	0
0	1	1	0	0	0
1	1	1	0	0	0
1	1	0	0	0	0
0	0	0	0	1	0

Figure 3: Illustration of horizontal run length count

C. Classification

Classification stage uses the features extracted in the feature extraction stage for deciding the class membership. Classification phase is the decision making phase of a character recognition engine. In this work, we have used k-NN classifier for recognition. In the K-Nearest Neighbour classifier, Euclidean distances from the candidate vector to stored vector are computed. The Euclidean distance between a candidate vector and a stored vector is given by equation (3),

$$d = \sqrt{\sum_{k=1}^{N} (x_k - y_k)^2} \qquad (3)$$

Here, N is the total number of features in feature set, x_k is the library stored feature value and y_k is the candidate feature value.

3. Practical and Comparative Results

In this study, for experimental analysis, we considered a part of standard Persian numeral dataset [14]. For experimental analysis, we considered 15,000 samples for training and 5,000 samples for testing of our method. These samples were extracted from different registration forms of entrance examinations of universities in Iran containing Iranian Postal and national codes. The images were scanned at 200 dpi resolution [14]. Because of writing styles of different individuals, samples sizes were very different, and as we discussed in Section 2 we normalized them. Using 15,000 samples for training, we tested our scheme on other 5,000 samples and obtained 99.82% accuracy. From the experiment, we got an accuracy of 100% when the 20,000 data were used as training and the same data set was used for testing. In another experiment, we divided our database (20,000 samples) into 4 subsets and testing is done on each subset using rest of the 3 subsets for training. The recognition rates for all the four test subsets of dataset are averaged to get the accuracy. We got the average accuracy of 99.90%. To compare the performance of our method we noted the performances of most of the works that were available for Persian numeral recognition. See Table I for details of comparison.

It may be noted from Table I that most of the existing works were evaluated on smaller datasets. Where we used 20,000 data for our experiment. The highest accuracy was obtained from the work due to Soltanzadeh et al. [7] but they have experimented with 8,918 samples and used 257 dimensional features.

TABLE 1: Comparison of Different Algorithm

Algorithm	Dataset size		Accuracy (%)	
	Train	Test	Train	Test
Sadri et al. [2]	7390	3035	-	94.14
Shirali-shahreza et al.[3]	2600	1300	-	97.80
Harifi., Aghagolzadeh [4]	230	500	-	97.60
Hosseini, Bouzerdum [5]	480	480	-	92.00
Mozaffari et al. [6]	2240	1600	98	91.37
Soltanzadeh, Rahmati [7]	4979	3939	-	99.57
Dehghan, Faez [8]	6000	4000	-	97.01
Ziaratban et al. [9]	6000	4000	100	97.65
Mozaffari et al. [10]	2240	1600	100	94.44
Mowlaei, Faez [11]	2240	1600	100	92.44
Mowlaei et al. [12]	2240	1600	99.29	91.88
Hamid Parvin, et al[15]	40000	2000	-	97.12
Hamid Parvin, et al[16]	60000	10000	-	98.89
Our proposed method	15000	50000	100	99.82
Our proposed method With 4 subset	15000	50000	100	99.90

We considered 20,000 data for our system and we obtained 99.82% and 99.90% accuracies using only 54 dimensional features. In our experiment (with the 99.90% accuracy), we observed confusion numerals in the recognition phase between some digits. The major confusions were amongst 2, 3 and 4. This happened because 2, 3 and 4 look like each other. Figure 4 shows the success and confusion rate, Fig. 5 shows the sample of digits that caused confusion.

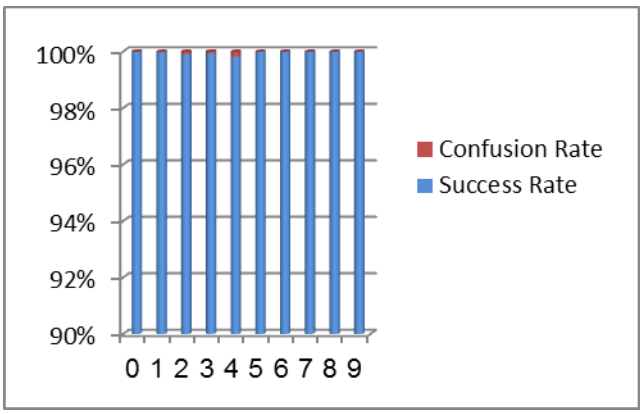

Figure 4: Success and Confusion Rate for Each Class

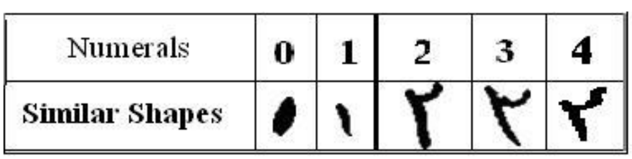

Figure 5: Similar Samples of Persian Digits

4. Conclusion

In this paper, an efficient feature extracting technique is proposed. In this respect we converted each character to the contour form then with use of block based technique three feature from each of these blocks were extracted and finally these feature set were used to character recognition by KNN classifier. From experimental results, it is evident that our features resulted good performances (99.82%, 99.90%). We noted that most of misclassified samples were from classes of 2, 3 and 4, which are similar shape. The recognition of such similar numerals was difficult even by human being. It is obvious that by removing confusion among few classes, we can achieve better performance.

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Authors profile.

Reza Azad is now studying B.Sc. in university of Shahid Rajaee Teacher Training, Tehran, Iran, from 2011 until now in computer software engineering technology. He takes the fourth place at university entering exam (Konkor Sarasary). Also he’s a member of IEEE, member of elites of the country, top and Honor student in university. Hi have 7 papers in the international conference and 4 papers in international journal. As a Reviewer in the 3rd IEEE International Conference on Computer and Knowledge Engineering. His research interests include image processing, artificial intelligence, handwritten character recognition, skin detection, face detection and recognition, human tracking, pattern recognition and localization of autonomous vehicles.

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