International Journal of Mechatronics, Electrical and Computer Technology

Vol. 4(10), Jan, 2014, Special Number, pp. 1133-1151, **ISSN**: 2305-0543
Available online at: http://www.aeuso.org

Persian Handwritten Digits Recognition Using Zoning and Histogram Projection with Different Dimension of Feature Vector

A. Nooraliei*[1] and B. Masoumi[2]

[1]Department of Electrical, Computer and IT engineering, Hamedan Branch, Islamic Azad University, Hamedan, IRAN

[2]Department of Electrical, Computer and IT engineering, Qazvin Branch, Islamic Azad University, Qazvin, IRAN

*Corresponding Author's E-mail: *Amir.nooraliei@iauh.ac.ir*

Abstract

In this paper, Persian handwritten digits reorganization using zoning features and projection histogram for extracting feature vectors with 21, 30, 69,105-dimensions is presented. In classification stage, support vector machines (SVM) with three linear kernels, polynomial kernel and Gaussian kernel have been used as a classifier. We tested presented algorithm on a subset of 8600 samples of the Hoda dataset that contained 80000 samples of Persian handwritten digits for performance analysis. Using 8000 samples in learning stage and another 600 samples in testing stage also the experiments have been performed on the entire data set. The results got with use of every three kernels of support vector machine and achieved maximum accuracy by using Gaussian kernel with gamma equal to 0.16. In preprocessing stage only image binarization is used and all the images of this dataset had been normalized at centers with size 40×40.The recognition rate, on the test datasets in order 91, 94.17, 97.83 and 98.67% was earned.

Keywords: Pattern recognition, Optical character recognition, Support vector machine, Persian handwritten digits.

1. Introduction

Statistical pattern recognition is one of subdivision of artificial intelligence. Today recognizing systems are used in different fields. Recognizing English handwritten words and digits are started from about 50 years ago and Arabic and Persian handwritten words and

International Journal of Mechatronics, Electrical and Computer Technology

Vol. 4(10), Jan, 2014, Special Number, pp. 1133-1151, **ISSN**: 2305-0543
Available online at: http://www.aeuso.org

digits are started from about 28 years ago. The optical characters recognition (OCR) has been started from recognizing the machine printed digits and characters and then has been developed for recognition of characters and digits handwritten. The handwritten digits Recognition is a vital component in many applications, such as bank checks reading, car plaque reading, zip code reading and reading the information from handwritten forms are a few examples[1, 2]. Hosseini and Bouzerdoum proposed a system that the Persian digit images are represented by 11 line segments (similar to 7-segments for English digits). The features are extracted by calculating the quantitative values corresponding to each of these lines and then combining these values in some specific manner. In this method, for segregating the digit pairs ''0–5'', ''7–8''and ''4–6'', some specific features and classifiers have been used[3, 4].

Mozaffari et al combined structural decomposition and statistical description and used nearest neighbor classifier for recognition. Also PCA for dimension reduction has been used[5]. Alirezanejad and Enayatifar method is based on the extraction of the new features of a number-narrowed image, and neural network for recognition has been accomplished[3, 6]. Rashnodi et al used box approach, ratio of length to width of image and discrete Fourier coefficient as extracted features and SVM as classifier. [1, 7]. Mowlaei et al used wavelet transform for feature extraction. The length of Feature vector was 64 and used neural network for classification stage. Because (۰, ۵) and (۲, ۳) are very similar to each other in Persian handwritten, therefore (۰) and (۲) are not used in Iran postal codes. They tested their method for classification of 8 classes on postal codes in IRAN[8].

Soltanzadeh and Rahmati present a novel method for recognition of Persian handwritten digits. In their method they used the image profile calculated at multiple orientations as the main feature each digits [3]. Ramana Murthy and Hanmandlu used zoning based feature extraction method and SVM as a classifier for Devanagari character recognition[9]. As feature extraction methods for digits and words recognition, zoning features, moments, Fourier descriptors, histogram projection, fractal code, profiles, templates and wavelet have been used[10, 11]. Feature type selects according to the application. Usually an ordinary

International Journal of Mechatronics, Electrical and Computer Technology

Vol. 4(10), Jan, 2014, Special Number, pp. 1133-1151, **ISSN**: 2305-0543
Available online at: http://www.aeuso.org

recognizing system contains three explicit sections which consist of: preprocessing, feature extraction and recognition which the exiting of every stage is the entrance of the next stage[7]. In the preprocessing stage, image binarization has been done. In feature extraction stage, zoning and histogram projection has been utilized. In the last part, for recognition SVM has been used. The stages of an ordinary recognition system are shown in figure 1 [6, 7].

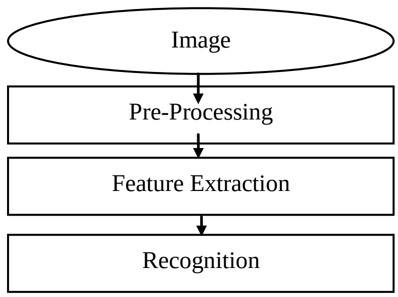


Figure 1: Optical character recognition systems

The handwritten characters recognition is one of the most interested topics in pattern recognition. Because to increasing the ever-increasing need to Persian writings recognition, need to recognition systems of optical characters becomes more. To achieve this aim, two features, histogram projection and zoning has been studied. In this paper SVM is used in classification stage as classifier with three linear, polynomial and Gaussian kernels[1, 12]. Should be noted that in considered system, only binarization technique in preprocessing stage has been utilized. Nooraliei combined zoning and histogram projection for Persian handwritten digits with 69-dimentional feature vectors[13].

In this paper, we used zoning and histogram projection for feature extraction but in zoning stage we divided image to 4×4, 5×5, 8×8 and 10×10 zones for different feature vector size and used these feature vectors in recognition stage. We compared accuracy and speed with deferent feature vector size. The organization of the paper is as follows: in section 2, the techniques of feature extraction are explained and section 3 classification stage is described, the results of tests are shown in section 4 and finally in last part the conclusion has been presented.

Vol. 4(10), Jan, 2014, Special Number, pp. 1133-1151, **ISSN**: 2305-0543
Available online at: http://www.aeuso.org

2. Proposed Method

For extracting the features in proposed method, which is the most important part in OCR systems, the following activities are carried out in order.

2.1. Preprocessing

The preprocessing stage contains image binarization. Frequently, binarization is accomplished before the recognition stage. Ideally, an input image should have two tones, like black and white pixels (commonly represented by 1 and 0, respectively).In this stage by using a threshold value, the gray level image converts to binary image. All images in dataset are normalized in center and their dimensions are 40×40. For extracting the features, the images divide to 4×4, 5×5, 8×8 and 10×10 segments, which totally the images divide to 16, 25, 64 and 100 zones 4×4, 5×5, 8×8 and 10×10. The images with dimensions 40×40 are divided as table 1.

TABEL 1: Dimensions and sizes of input image and zones

Image size	Number of zones	Zones size	Feature vector size
40×40	16	4×4	**16**
	25	5×5	**25**
	64	8×8	**64**
	100	10×10	**100**

In each image, some zones contain part of image and other parts are empty, however all zones are considered for extraction the feature [1, 10, 14].

International Journal of Mechatronics, Electrical and Computer Technology

Vol. 4(10), Jan, 2014, Special Number, pp. 1133-1151, **ISSN**: 2305-0543
Available online at: http://www.aeuso.org

2.2. Zoning

In this method, the average of image intensity in every zone is calculated separately and is considered as a feature of its zone. This feature alone is not high performance and need to combine with other features. Table II shows the extraction order of parameters from zones and figure 2 shows zoning and averaging of zones intensity [9, 10].

TABEL 2: The feature extracted from zones

Box Numbers	Feature vector	Feature vector	Feature vector	Feature vector
Box-1	z_1	z_1	z_1	z_1
Box-2	z_2	z_2	z_2	z_2
……………	……………	……………	……………	……………
Box-21	z_{21}	z_{21}	z_{21}	z_{21}
……………		……………	……………	……………
Box-25		z_{25}	z_{25}	z_{25}
……………			……………	……………
Box-64			z_{64}	z_{64}
……………				……………
Box-100				z_{100}

International Journal of Mechatronics, Electrical and Computer Technology

Vol. 4(10), Jan, 2014, Special Number, pp. 1133-1151, **ISSN**: 2305-0543
Available online at: http://www.aeuso.org

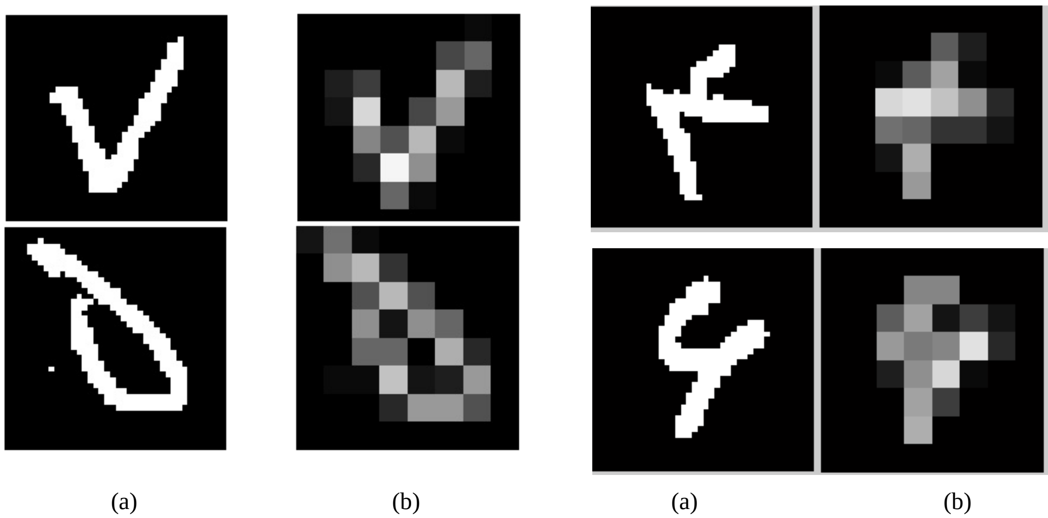


Figure 2: Zoning of binary image. (a) Original binary image. (b) A 8×8 grid that's 64 averaged zones.

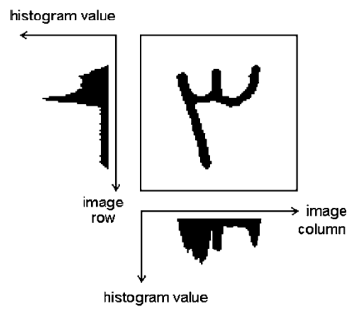
2.3. Histogram Projection

Histogram projection was introduced by Glauberman in a hardware optical character recognition in 1956. Today, this technique used for segmenting characters, words and lines between texts or for distinguishing the rotation of scanned texts. For a horizontal projection, $y(x_i)$ is the number of pixels with $x = x_i$ and is the same for vertical projection. Figure 3 shows the vertical and horizontal histogram projection on 3 samples of dataset. By using a fixed number of bins on each axis, this feature can be a scale independent. In this paper, we extracted from each histogram projection two values of variance, maximum and sum of values of bins which totally extracted five features in this section. According to the above steps, 16, 25, 64 and 100 features extracted from zoning and five features extracted from histogram projection which totally 21, 30, 69 and 105 features are extracted from each image. On the other hand, for each input image, the features with 21, 30, 69 and 105 dimensions is considered [10, 15].

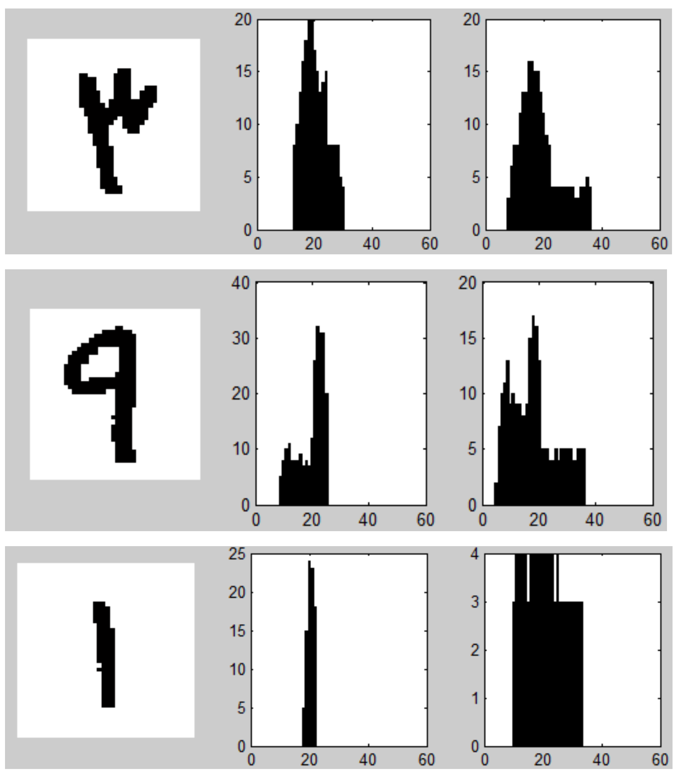
International Journal of Mechatronics, Electrical and Computer Technology

Vol. 4(10), Jan, 2014, Special Number, pp. 1133-1151, **ISSN**: 2305-0543

Available online at: http://www.aeuso.org



(a)



(b) (c) (d)

Figure 3: Vertical and horizontal histogram projection. (a) Vertical and horizontal projection histogram for digit of 3. (b) Original binary

International Journal of Mechatronics, Electrical and Computer Technology

Vol. 4(10), Jan, 2014, Special Number, pp. 1133-1151, **ISSN**: 2305-0543
Available online at: http://www.aeuso.org

3. Support vector machine

Supporter vector machines (SVMs) are particular classifiers which are based on margin-maximization rule. For nonlinear problems, SVM uses of kernel trick for making nonlinear boundaries. The idea behind kernels is to map training data nonlinearly into a higher-dimensional feature space via a mapping function and making a hyper plane which maximizes the margin. Making the decision linear surface in the feature space only need the evaluation of dot products $\phi(x).\phi(y) \equiv k(x,y)$ where k(x, y) is called kernel function. The separator function of a binary SVM is computed by (1):

$$f(x) = \sum_{i=1}^{l} y_i \alpha_i k(x, x_i) + b \qquad (1)$$

Where l is the number of learning patterns, yi is the target value of learning pattern x (+1 for the first class and -1 for the second class), b is a bias and k(x, xi) is a kernel function. Also multi class SVMs like Libsvm is existing for classification more than two classes [1, 16]. The details of SVM can be found in[4, 17]. The input features set were 25, 29, 69 and 105 dimensions. All of SVMs are trained by training feature set and the results are shown by use of separate test data. We got the best results with gamma = 0.16 and polynomial kernel. Gamma value achieved with try and error. Three types of kernels polynomial kernel, RBF kernel and Linear Kernel are frequently used. They are computed by table 3 [12, 18, 19].

TABEL 3: SVM kernels

Kernels	Definition
Linear	$k(x, x_i) = x.x_i$
Polynomial	$k(x, x_i, \gamma, p) = (\gamma.x.x_i)^p$
RBF	$k(x, x_i, \gamma) = \exp(-\gamma.\lVert x - x_i \rVert^2)$

Where p, are the parameters of the corresponding kernels. Usually the default P value is 3.

International Journal of Mechatronics, Electrical and Computer Technology

Vol. 4(10), Jan, 2014, Special Number, pp. 1133-1151, **ISSN**: 2305-0543
Available online at: http://www.aeuso.org

4. Experimental result

In this paper, we used of Persian digits dataset with 8600 samples for test analysis. These samples were collected from distributed different forms among Tehran university bachelor students that every person writes 0 to 9 on the forms in the shape of handwritten and also the forms were scanned in 300 dpi resolution and all in the center of the image and have 40×40 size.

4.1. Dataset

We used of 8000 samples for training and 600 samples for testing. Figure 4 shows some of handwritten digits samples of this dataset. The 4 and 6 digits written with two writing shape in this dataset [2].

(a)

(b)

Figure 4: Some of handwritten digits in dataset. (a) Train samples. (b) Test samples.

4.2. Performance

We used 8000 samples for training and then tested on the other 600 samples that %91, %94.17, %97.83 and %98.67 accuracy were achieved. We Also achieved %99.73 accuracy when 8000 samples used for training and testing also got %100 accuracy when use of 8600 samples for training and testing. The performance results of feature extract techniques which are presented shown at table 4. Also we used 60000 samples for training and 20000 samples

International Journal of Mechatronics, Electrical and Computer Technology

Vol. 4(10), Jan, 2014, Special Number, pp. 1133-1151, **ISSN**: 2305-0543
Available online at: http://www.aeuso.org

for test from dataset with 80000 samples. The experimental results of large dataset shown in table 5. Thus, the recognition accuracy of each digit would be according to the Table 7-11. For comparing the effectiveness of our method, we compared it to the last best method which was done on this dataset of Persian handwritten digits and got an accuracy increase at %3.67 for a 105-dimension vector. The experimental results on the train and test data and all of the dataset are shown at table 4.

Also we tested presented algorithm on large dataset that contained 80000 samples and compare performance of it with other methods on same or different dataset. We achieved 98.89 accuracy on large dataset with use 105-D feature vector. There are two recognition rates better than proposed method that only one of them used large dataset and 163-D feature vector. Furthermore According to length of feature vector, the difference is 0.05. Also another used 257-D feature vector. The experiments of results are shown on table 5 for large dataset.

TABLE 4: Results on Dataset with 8600 Samples

Technique				**dataset**		**accuracy**
	Classifier	**Feature Vector Size/Reduced**	**Feature Reduction**	**train**	**test**	test
Seied Hasan Nabavi Karizi, et al [20]	NN	81	N	1800	530	**91**
Taghavi Morteza, et al [2]	NN	22	N	8000	600	**95**
Proposed Method	SVM	21	N	8000	600	**91**
		30	N	8000	600	**94.17**
		69	N	8000	600	**97.83**
		105	N	8000	600	98.67

Vol. 4(10), Jan, 2014, Special Number, pp. 1133-1151, **ISSN**: 2305-0543
Available online at: http://www.aeuso.org

TABLE 5: Results on Dataset with 80000 Samples

Technique	dataset					accuracy
	Classifier	Feature Vector Size/Reduced	Feature Reduction	train	test	test
Mowlaei, et al [8]	NN	64	N	2240	1600	**91.81**
Reza Ebrahimpour, et al [21]	NN	1600/30	PCA	6450	2150	**91.98**
Alirezanejad Mehdi, et al [6]	NN	48	N	40000	20000	**92.7**
Sadri, et al [22]	SVM	64	N	7390	3035	**94.14**
Sabri Mahmoud [23]	HMM	120	N	16675	4463	**94.35**
Saeed Mozaffari, et al [5]	NNC	72/52	PCA	280	200	**94.44**
Abbas Harifi, et al [24]	NN	12	N	230	500	**97.36**
Omid Rashnodi, et al [1]	SVM	154	N	60000	20000	**98.84**
Proposed Method	SVM	105	N	60000	20000	98.89
Omid Rashnodi, et al [7]	SVM	163	N	60000	20000	**98.94**
Hasan Soltanzadeh, et al [25]	SVM	257	N	4974	3939	**99.57**

International Journal of Mechatronics, Electrical and Computer Technology

Vol. 4(10), Jan, 2014, Special Number, pp. 1133-1151, **ISSN**: 2305-0543

Available online at: http://www.aeuso.org

TABLE 6: Speed of extracting feature

Number of image	Zone size	Zoning(sec)	Histogram Projection(sec)	Total(sec)
1	4×4	0.03	0.08	**0.11**
	5×5	0.06		**0.14**
	8×8	0.14		**0.22**
	10×10	0.2		**0.28**

TABLE 7: Confusion matrix and Accuracy recognition of Persian digits for feature vector 21-D

	0	9	8	7	6	5	4	3	2	1	digits
	0	**0**	1	1	2	**0**	**0**	**0**	0	56	**1**
	0	**0**	**0**	**0**	**0**	**0**	**0**	**0**	60	**0**	**2**
	0	**0**	**0**	1	**0**	**0**	**0**	58	1	**0**	**3**
	0	**0**	**0**	**0**	**0**	1	54	4	0	1	**4**
	0	**0**	**0**	**0**	**0**	44	8	8	**0**	**0**	**5**
	1	2	**0**	**0**	56	**0**	**0**	**0**	**0**	1	**6**
	8	**0**	4	49	**0**	**0**	**0**	2	**0**	**0**	**7**
	0	6	53	**0**	**0**	**0**	**0**	**0**	**0**	1	**8**
	0	58	1	**0**	**0**	**0**	**0**	**0**	**0**	1	**9**
Accuracy	58	**0**	**0**	1	**0**	**0**	**0**	**0**	**0**	1	**0**
%91	%96.67	%96.67	%88.33	%81.67	%93.33	%73.33	%90.00	%96.67	%100.00	%93.33	**Accuracy recognition**

International Journal of Mechatronics, Electrical and Computer Technology

Vol. 4(10), Jan, 2014, Special Number, pp. 1133-1151, **ISSN**: 2305-0543

Available online at: http://www.aeuso.org

TABLE 8: Confusion matrix and Accuracy recognition of Persian digits for feature vector 30-D

	0	**9**	**8**	**7**	**6**	**5**	**4**	**3**	**2**	**1**	**digits**
	0	0	0	0	2	0	0	0	0	58	**1**
	0	0	0	0	0	0	0	0	60	0	**2**
	0	0	1	3	0	0	1	55	0	0	**3**
	0	0	0	0	0	4	54	2	0	0	**4**
	0	0	0	0	0	52	6	1	1	0	**5**
	0	0	0	0	57	0	0	0	0	3	**6**
	1	0	1	54	0	0	1	3	0	0	**7**
	0	0	60	0	0	0	0	0	0	0	**8**
	0	59	0	0	0	0	0	0	0	1	**9**
Accuracy	56	1	0	1	0	0	0	1	1	0	**0**
%94.17	**%93.33**	**%98.33**	**%100.00**	**%90.00**	**%95.00**	**%86.67**	**%90.00**	**%91.67**	**%100.00**	**%96.67**	**Accuracy recognition**

International Journal of Mechatronics, Electrical and Computer Technology

Vol. 4(10), Jan, 2014, Special Number, pp. 1133-1151, **ISSN**: 2305-0543
Available online at: http://www.aeuso.org

TABLE 9: Confusion matrix and Accuracy recognition of Persian digits for feature vector 69-D

	0	9	8	7	6	5	4	3	2	1	digits
	0	0	0	0	1	0	0	0	0	59	**1**
	0	0	0	0	0	0	0	0	60	0	**2**
	0	0	1	0	0	0	0	59	0	0	**3**
	0	0	0	0	0	1	58	1	0	0	**4**
	0	0	0	0	0	57	2	1	0	0	**5**
	0	0	0	0	59	1	0	0	0	0	**6**
	2	0	2	56	0	0	0	0	0	0	**7**
	0	0	60	0	0	0	0	0	0	0	**8**
	0	60	0	0	0	0	0	0	0	0	**9**
Accuracy	59	0	0	0	0	0	0	0	1	0	**0**
%97.83	**%98.33**	**%100.00**	**%100.00**	**%93.33**	**%98.33**	**%95.00**	**%96.67**	**%98.33**	**%100.00**	**%98.33**	**Accuracy recognition**

International Journal of Mechatronics, Electrical and Computer Technology

Vol. 4(10), Jan, 2014, Special Number, pp. 1133-1151, **ISSN**: 2305-0543

Available online at: http://www.aeuso.org

TABLE 10: Confusion matrix and Accuracy recognition of Persian digits for feature vector 105-D

	0	9	8	7	6	5	4	3	2	1	digits
	0	0	0	0	0	0	0	0	0	60	**1**
	0	0	0	0	0	0	0	0	60	0	**2**
	0	0	0	0	0	0	0	59	1	0	**3**
	0	0	0	0	0	0	59	1	0	0	**4**
	0	0	0	0	0	59	1	0	0	0	**5**
	0	1	0	0	58	0	0	0	0	1	**6**
	1	0	0	59	0	0	0	0	0	0	**7**
	0	0	60	0	0	0	0	0	0	0	**8**
	0	60	0	0	0	0	0	0	0	0	**9**
Accuracy	58	0	0	0	0	0	0	0	2	0	**0**

International Journal of Mechatronics, Electrical and Computer Technology

Vol. 4(10), Jan, 2014, Special Number, pp. 1133-1151, **ISSN**: 2305-0543

Available online at: http://www.aeuso.org

98.67%	%96.67	%100.00	%100.00	%98.33	%96.67	%98.33	%98.33	%98.33	%100.00	%100.00	**Accuracy recognition**

Vol. 4(10), Jan, 2014, Special Number, pp. 1133-1151, **ISSN**: 2305-0543
Available online at: http://www.aeuso.org

TABLE 11: Confusion matrix and Accuracy recognition of Persian digits for feature vector 105-D on Dataset with 80000 Samples

	0	**9**	**8**	**7**	**6**	**5**	**4**	**3**	**2**	**1**	**digits**
	1	0	0	0	3	0	0	0	6	1989	**1**
	0	0	0	0	0	0	13	54	1925	8	**2**
	0	0	0	1	0	3	37	1920	39	0	**3**
	0	0	0	0	1	1	1978	19	1	0	**4**
	4	0	6	0	1	1987	0	0	0	0	**5**
	0	5	0	5	1984	0	6	0	0	0	**6**
	0	0	0	1998	0	0	1	0	0	0	**7**
	0	0	1998	0	1	0	0	0	0	0	**8**
	0	1995	2	0	3	0	0	0	0	0	**9**
Accuracy	1999	0	0	0	0	0	0	1	0	0	**0**
98.89%	%99.95	%99.75	%99.95	%99.95	%99.20	%99.45	%98.90	%96.00	%96.25	%99.50	**Accuracy recognition**

CONCLUSION

In this paper, a method of effective feature extraction is presented. In test results, the extracted features with this method on test data 98.67% and also on all data set accuracy %100 is observed. As well as 98.89% accuracy achieved on large dataset. These results are taken with use of 105-dimension feature vector in support vector machine. The most false recognizing in samples related to digits classes 3, 4, 5 and 7 which were more due to existence of noisy data in dataset. The recognition of such similar or corrupted numerals is difficult even by human being. To achieve better results which can be less time for testing, feature vector with smaller dimensions and more accuracy

Vol. 4(10), Jan, 2014, Special Number, pp. 1133-1151, **ISSN**: 2305-0543
Available online at: http://www.aeuso.org

recognition combination methods which are extracting features and classifiers, using new feature and using more methods in a preprocessing stage can be applied.

References

[1] O. Rashnodi, H. Sajedi, and M. S. Abadeh, "Persian Handwritten Digit Recognition using Support Vector Machines," International Journal of Computer Applications, vol. 29, 2011.

[2] M. Taghavi, S. Mohamdainia, and R. haghmaram, "Conditional use of classifiers two and ten class for Persian and Arabic handwritten digits classification," in 3rd Iranian conference on electrical and electronic engineering, 2012, pp. 1-5.

[3] R. Ebrahimpour, M. R. Moradian, A. Esmkhani, and F. M. Jafarlou, "Recognition of Persian handwritten digits using Characterization Loci and Mixture of Experts," JDCTA, vol. 3, pp. 42-46, 2009.

[4] H. M. M. Hosseini and A. Bouzerdoum, "A combined method for Persian and Arabic handwritten digit recognition," in Intelligent Information Systems, 1996., Australian and New Zealand Conference on, 1996, pp. 80-83.

[5] S. Mozaffari, K. Faez, and M. Ziaratban, "Structural decomposition and statistical description of Farsi/Arabic handwritten numeric characters," in Document Analysis and Recognition, 2005. Proceedings. Eighth International Conference on, 2005, pp. 237-241.

[6] M. Alirezanejad and R. Enayatifar, "Farsi digit recognition via features extraction," International Journal of the Physical Sciences, vol. 6, pp. 3198-3204, 2011.

[7] O. Rashnodi, H. Sajedi, and M. S. Abadeh, "Using Box Approach in Persian Handwritten Digits Recognition," International Journal of Computer Applications, vol. 32, 2011.

[8] A. Mowlaei, K. Faez, and A. T. Haghighat, "Feature extraction with wavelet transform for recognition of isolated handwritten Farsi/Arabic characters and numerals," in Digital Signal Processing, 2002. DSP 2002. 2002 14th International Conference on, 2002, pp. 923-926.

[9] O. Ramana Murthy and M. Hanmandlu, "Zoning based Devanagari Character Recognition," International Journal of Computer Applications, vol. 27, 2011.

[10] Ø. Due Trier, A. K. Jain, and T. Taxt, "Feature extraction methods for character recognition-a survey," Pattern recognition, vol. 29, pp. 641-662, 1996.

[11] M. M. Javidi, R. Ebrahimpour, and F. Sharifizadeh, "Persian handwritten digits recognition: A divide and conquer approach based on mixture of MLP experts," International Journal of the Physical Sciences, vol. 6, pp. 7007-7015, 2011.

Vol. 4(10), Jan, 2014, Special Number, pp. 1133-1151, **ISSN**: 2305-0543
Available online at: http://www.aeuso.org

[12] J. Shawe-Taylor and N. Cristianini, Kernel methods for pattern analysis: Cambridge university press, 2004.

[13] A. Nooraliei, "Persian handwritten digits recognition by using zoning and histogram projection," in AI & Robotics and 5th RoboCup Iran Open International Symposium (RIOS), 2013 3rd Joint Conference of, 2013, pp. 1-5.

[14] S. N. Srihari and G. Ball, "An assessment of Arabic handwriting recognition technology," in Guide to OCR for Arabic Scripts, ed: Springer, 2012, pp. 3-34.

[15] R. P. dos Santos, G. S. Clemente, T. I. Ren, and G. D. Cavalcanti, "Text line segmentation based on morphology and histogram projection," in Document Analysis and Recognition, 2009. ICDAR'09. 10th International Conference on, 2009, pp. 651-655.

[16] C.-C. Chang and C.-J. Lin, "LIBSVM: a library for support vector machines," ACM Transactions on Intelligent Systems and Technology (TIST), vol. 2, p. 27, 2011.

[17] V. Vapnik, The nature of statistical learning theory: springer, 2000.

[18] C. J. Burges, "A tutorial on support vector machines for pattern recognition," Data mining and knowledge discovery, vol. 2, pp. 121-167, 1998.

[19] B. Scholkopf and A. Smola, "Learning with kernels," ed: MIT press Cambridge, 2002.

[20] S. H. N. Karizi, R. Ebrahimpor, and E. Kabir, "Application combining classifiers in Persian handwriting digits recognition," in 3rd Conference on Machine Vision and Image Processing, Tehran, 2005.

[21] R. Ebrahimpour and F. Sharifizadeh, "Persian handwritten digit recognition with classifier fusion: class conscious versus class indifferent approaches," Tc, vol. 1, p. 1, 2009.

[22] J. Sadri, C. Y. Suen, and T. D. Bui, "Application of support vector machines for recognition of handwritten Arabic/Persian digits," in Proceedings of Second Iranian Conference on Machine Vision and Image Processing, 2003, pp. 300-307.

[23] S. Mahmoud, "Recognition of writer-independent off-line handwritten Arabic (Indian) numerals using hidden Markov models," Signal Processing, vol. 88, pp. 844-857, 2008.

[24] A. Harifi and A. Aghagolzadeh, "A new pattern for handwritten Persian/Arabic digit recognition," in International Conference on Information Technology (ICIT2004), Istanbul, Turkey December, 2004.

[25] H. Soltanzadeh and M. Rahmati, "Recognition of Persian handwritten digits using image profiles of multiple orientations," Pattern Recognition Letters, vol. 25, pp. 1569-1576, 2004.