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RESEARCH NOTE

A Modfied Self-organizing Map Neural Network to Recognize Multi-font Printed Persian Numerals

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A B S T R A C T

This paper proposes a new method to distinguish the printed digits, regardless of font and size, using neural networks.Unlike our proposed method, existing neural network based techniques are only able to recognize the trained fonts. These methods need a large database containing digits in various fonts. New fonts are often introduced to the public, which may not be truly recognized by the Optical Character Recognition (OCR). Therefore, the existing OCR systems may need to be retrained or their algorithm be updated. In this paper we propose a self-organizing map (SOM) neural network powered by appropriate features to achieve high accuracy rate for recognizing printed digits problem. In this method, we use a limited sample size for each digit in training step. Two expriments are designed to evaluate the performance of the proposed method. First, we used the method to classify a database including 2000 printed Persian samples with twenty different fonts and ten different sizes from which 98.05% accuracy was achieved. Second, the proposed method is applied to unseen data with different fonts and sizes with those used in training data set. The results show 98% accuracy in recognizing unseen data.

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1. INTRODUCTION

Digits recognition is a task in Optical Character Recognition (OCR) systems. Scientists and engineers have developed various approaches in image processing and pattern recognition techniques to recognize digits. These techniques lead to develop various applications which are dependent on digits recognition, such as recognizing bank notes and car plate numbers [1, 2].

In different languages, the digits recognition is an attractive problem for researchers. Both of handwritten and printed digit recognition were developed in the literature. Unlike Arabic/Persian, there are many Latin digit recognition studies using different methods with good results [3-7]. Though, techniques for recognizing printed digits are fewer than handwrittens.

Classifier methods based on learning from samples have been extensively used for character recognition. Statistical methods which are based on artificial neural networks, and use support vector machine (SVM) are examples of applied digits recognition techniques [8].

Since neural networks are proper for classifying data, they have been excessively used for recognizing digits. Shirvastava et al. have proposed a method which the sums of pixels' values through the horizontal lines were drawn at various distances as feature vector [9]. Using this feature vector and applying it to a neural network with back propagation learning method achieved 85.83% accuracy. In another work, 96.6% accuracy has been obtained by using feed forward neural network [10]. The feature vector contains information about digits shape such as coordinates of bounding box, centroid and equiv-diameter. Using multilayer neural networks, a handwritten digits recognition system was introduced which extracts features based on digits shape [11]. The classification accuracy for the digits in the MNIST database of 60,000 training samples and 10,000 test samples has reached 80%. This database contains images of 250 different handwritten digits [12]. A

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Convolutional Recursive Modified SOM (Self-Organizing Map) with improved initialization process in recognizing handwritten digits and topology preservation was proposed in Ref. [13]. After evaluating this method on MNIST database, its superiority over the earlier SOM-based algorithms became clear. Researches have proposed another method to recognize printed Persian digits using fuzzy min-max neural network [14]. They applied the digits which are descripted by geometric central moments. The method achieves 98.57% accuracy for trained samples and is resistant to changes in scale, translation and rotation. An ensemble classifier was used to recognize Persian handwritten digits [15]. A complementary set of 115 features was extracted from TMU digits database and the recognition rate of 95.88% was obtained. A composed method has been introduced to distinguish multi-font printed Persian digits [16]. In this method, average vector distance and angle of each zone of image are used to describe the digits and fuzzification is applied to dominate variations in different fonts. This method gained 97.5% accuracy on a dataset consisted of 216 samples in 24 variant fonts. Montazer et al. used a Mamdani neuro fuzzy inference engine to recognize multi-font Persian digits [17]. Experimental results showed 97% accuracy for all Farsi numeral characters in 33 various fonts except numeral 4.

All the presented methods suffer a major problem, they are sensitive to font, size and mode (Italic, Bold and Regular) of digits [18]. This problem casuses a less accuracy when a different fonts set is detected in testing phase. To overcome this problem, existing methods use too large databases in training phase because they contain different fonts and sizes. Also, new fonts are made over time and the existing digits recognition systems may not be able to work properly with these new fonts and should be modified or retrained.

In this system, a simple approach is applied to form the feature vector. The digits are binary images. Number of 1s in various columns and rows of binary image of each digit can be used as feature vector to descript the digit. The feature vector guarantees all the samples in a class are similar to each other (not identical) but are different from those in other classes. Then, digits represented by the feature vectors are classified using SOM. In generic SOM, Euclidean distance is used to compare instances of a class, but in this paper a similarity measure is used instead. This modification causes some advantages, it reduces required samples for training to a small set. In addition, in testing phase the system will be able to recognize digits, in different sizes, fonts and modes in high accuracy.

The rest of the paper is organized in four Sections. The methodology is explained in Section 2. Section 3 describes the implementation results. At last, Section 4 concludes the paper.

2. METHODOLOGY

The binary image of a digit is used to recognize it in this research. Several preprocessing operations, such as removing noise, segmenting the digit from background and resizing for normalization, are performed on the binary image to increase the accuracy of detection. Then, the number of ones in rows and columns of each binary image is extracted as the feature vector. In the following, these vectors are classified based on their similarity. Considering the fact that the characteristics of data in the feature vector, a proper similarity measure should be selected. In the proposed method, the representative of each class is created by training a SOM neural network. Finally, the proposed method is evaluated by test data in testing phase.

2. 1. Data Acuisition For first step of our recognition system, we should supply input binary images of digits. Therefore, we use a database containing binary samples of each digit in twenty different fonts: "B Mitra, B Nazanin, B Zar, B Davat, B Roya, B Badr, Hamid, B Compset, B Fantezy, B Ferdosi, B Koodak, B Lotus, B Shiraz, B Titr, B Traffic, B Yagut, Baran, Karim, B Elham and B Esfehan" in sizes 14 to 32 (even numbers) randomly either in Regular or Bold face. There are totally 2000 samples in the database. Some examples of various fonts in the database are shown in Figure 1. A few samples in each class are used in training phase. Since in Persian, numbers 4, 5 and 6 have various shapes (see Figure 2) we need to have training samples for each of them.

2. 2. Pre-processing The following steps are taken in pre-processing stage to improve the quality of extracted feature:

- Applying a median filter to remove noise.
- Extracting the smallest rectangle surrounding the digit to separate the digit from background. This rectangle may not have the same size for all samples because of various fonts and sizes.
- Resizing the image by the nearest neighborhood interpolation method [19] to 30x30 pixels similar to [20].

Figure 3 shows an example of the pre-processing process for digit 5.

2. 3. Feature Extraction Performance of the recognition system presented in this study is largely dependent on feature extraction. So, the extracted features must have some properties, describe all digit classes and be able to represent a similar characteristic for each class despite difference in size and font of samples. As discussed in Section 2.1, pixels of background are displayed with "0" and digit is shown with "1" pixels.

Font	Numerals	Font	Numerals
B Koodak	۰۱۲۳۴۵۶۷۸۹	B Nazanin	۰۱۲۳۴۵۶۷۸۹
B Lotus	۰۱۲۳۴۵۶۷۸۹	B Mitra	۰۱۲۳۴۵۶۷۸۹
B Shiraz	۰۱۲۳٤٥٦۷۸۹	B Zar	۰۱۲۳۴۵۶۷۸۹
B Titr	۰۱۲۳۴۵۶۷۸۹	B Davat	۰۱۲۳٤٥٦۷۸۹
B Traffic	۰۱۲۳٤۵۶۷۸۹	B Roya	۰۱۲۳۴۵۶۷۸۹
B Yagut	۰۱۲۳۴۵۶۷۸۹	B Badr	۰۱۲۳۴۵۶۷۸۹
2 Baran	۰۱۲۳٤٥٦۷۸۹	2 Hamid	۰۱۲۳٤٥٦۷۸۹
2 Karim	۰۱۲۳۴۵۶۷۸۹	B Compset	۰۱۲۳۴۵۶۷۸۹
B Elham	۰۱۲۳۴٥٦۷۸۹	B Fantezy	۰۱۲۳٤٥٦۷۸۹
B Esfehan	۰۱۲۳٤٥٦۷۸۹	B Ferdosi	۰۱۲۳۴۵۶۷۸۹

Figure 1. Examples of Persian digits from different varieties of fonts in the database

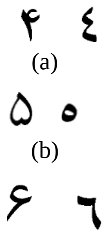

Figure 2. Various shapes of: a) number 4, b) number 5, and c) number 6 in Persian.

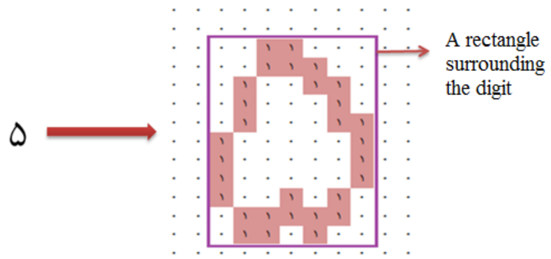

Figure 3. A printed example of digit 5 in Persian and a rectangle surrounding it to form the feature vector.

The feature vector is extracted by counting number of 1s in each row and column. In the pre-processing stage, we resized all images to 30x30 pixels, so feature vectors have a length of 60 (Figure 4). The feature vectors associated with various digits in four different fonts are illustrated in Figure 5.

As shown in Figure 5, all feature vectors have the same length but they might have different amplitude variations. If the digits of same class had different fonts, the feature vectors would have different local maxima and minima.

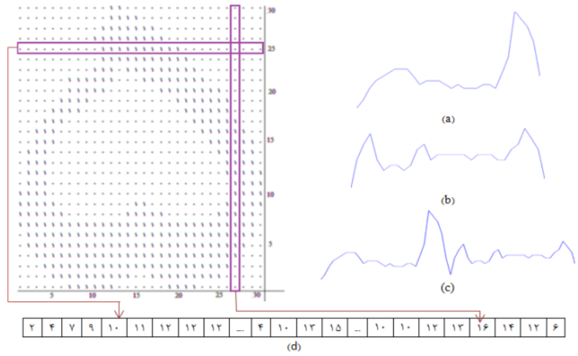

Figure 4. An example of feature extraction for number "5" in font B Zar in Persian: a) summation of the binary patterns in rows, b) summation of the binary patterns in columns, c) concatenation of (a) and (b), d) the extracted feature vector

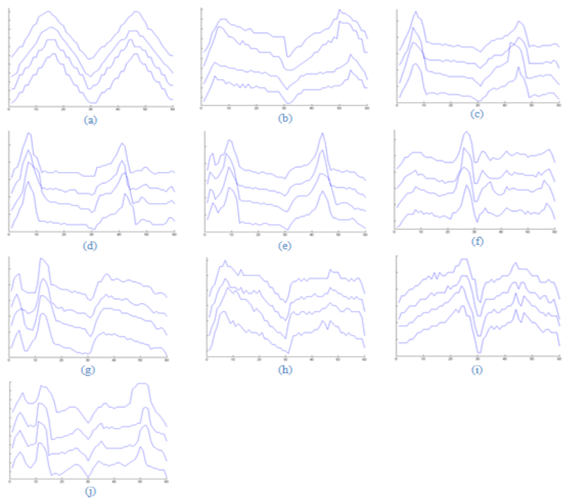

Figure 5. The extracted feature vectors corresponding to digits a) 0, b) 1, c) 2, d) 3, e) 4, f) 5, g) 6, h) 7, i) 8, j) 9. The features of four various patterns of a digit in different fonts including "B Nazanin", "B Zar", "B Mitra", and "B Roya" are demonstrated in each of the sub-figures from top to bottom.

Hence, employing distance measures such as Euclidean distance may not be appropriate for classification. It is necessary to compare and classify feature vectors using a suitable similarity measure.

2. 4. Similarity Measure A similarity measure is used to determine the similarity between two time series. There are various similarity measures in literature, each of which is suitable for certain applications. In Ref. [21], additional information about similarity measures can be found. In this study, we need a similarity measure which is able to compare time series with the same lengths but different amplitudes, so the Jensen similarity measure can be a appropriate choice.

For two verctors $p = \{p1, p2, ..., pk\}$ and $Q = \{q1, q2, ..., qk\}$ associated with the feature vector of two digits, the Jensen function is defined as below:

$$J(p,q) = \frac{1}{2}\sum_{i=1}^{k}\{p_i^{'}\log_2 p_i^{'} + q_i^{'}\log_2 q_i^{'} - (p_i^{'} + q_i^{'})\log_2(\frac{p_i^{'} + q_i^{'}}{2})$$
$$where\ p_i^{'} = \frac{p_i}{\sum_{i=1}^{k} p_i}\ and\ q_i^{'} = \frac{q_i}{\sum_{i=1}^{k} q_i} \quad (1)$$

The equation gives a value between 0 and 1. If two time series P and Q are totally similar, the Jensen will return 0 as output.

Table 1 shows similarity values resulted by Jensen to evaluate performance of this measure for current application (font 2 Hamid). The results reveal that Jensen can recognize the feature vectors from same class (resulting zero) and also can consider two nonidentical vectors as unlike (resulting a number above 0.1).

2. 5. Structure of Network In this paper, to classify the digits, we apply the SOM neural network. This network has two layers, one input and one output [22, 23]. The input layer includs 60 neurons which is equal to length of the feature vectors. The output layer needs ten neurons at least. However, we have to consider three extra classes for numbers 4, 5 and 6 as each of them have two different apperances in Persian. So, this network will have 13 neurons in output layer.

For training the SOM neural network, the sample containing highest average similarity within the class is chosen as the weight for the associated neuron. In other words, among the training samples in each class, the one which has maximum similarity with all other samples from the same class is chosen for setting the representative neroun of the class.

Once a sample is applied to the trained SOM, it is assigned to the class which its representative neuron has maximum similarity with.

3. RESULTS

We consider various binary images of Persian digits to evalute accuracy of the developed system in digit recognition. Two experiments are designed to evaluate performance of the proposed method. First, one uses test data with the same font and size of train. The second experiment evalutes the method by data in different fonts and sizes compared with those used in training data set. The data set in the second experiment contains 10 samples per digit with fonts of “B Fantezy” and “B Arabic style” and sizes of 8, 10, 12, 34, and 38.

We consider precision (PR), sensitivity (SEN), F-Measure (FM), and total F-Measure (TFM) in the evaluation process of the experiments as stated below [24].

Sensitivity is a statistical measure that shows the performance of a binary calssification test, which is defined as the fraction of samples which have been correctly recognized (TP) over total samples in a class (Equation (2)).

As Equation (3) shows, precision is defined as the fraction of the TP samples over all recognized samples:

$$SEN = \frac{TP}{TP + FN} \quad (2)$$

$$PRE = \frac{TP}{TP + FP} \quad (3)$$

Notabely, False Negative (FN) is number of predicting positive samples as negative. False Positive (FP) occurs when a negative sample is predicted as positive.

F-Measure is defined as harmonic mean precision and sensitivity (Equation (4)). As Equation (5) shows total F-Measure is sum of the fraction of multiplying F-Measure over true predicted samples from each class among total samples.

$$FM = 2 * \frac{PR * SEN}{PR + SEN} \quad (4)$$

$$TFM = \sum \frac{TP}{n} * FM \quad \text{n represent the total data} \quad (5)$$

TABLE 1. Evaluated similarity between feature vector extracted from different digits using Jensen similarity measure

	Zero	**One**	**Two**	**Three**	**Four**	**Five**	**Six**	**Seven**	**Eight**	**Nine**
Zero	0	0.145	0.127	0.207	0.181	0.197	0.282	0.131	0.139	0.119
One		0	0.143	0.183	0.166	0.113	0.143	0.110	0.141	0.103
Two			0	0.081	0.181	0.200	0.318	0.187	0.216	0.126
Three				0	0.142	0.231	0.303	0.120	0.288	0.207
Four					0	0.248	0.156	0.116	0.236	0.143
Five						0	0.143	0.103	0.117	0.175
Six							0	0.181	0.186	0.130
Seven								0	0.106	0.107
Eight									0	0.172
Nine										0

Table 2 shows digit recognition rate, i.e. accuracy (AC), and TFM in two experiments. Accuracy or recognition rate for each digit is shown in Table 3. The results show that the proposed method has a weakness for recognizing number 2. This is due to diversity of appearance of the digits in different fonts.

Table 4 shows measured values of PR, SEN and FM for each digit in the first and second experiments. Each digit has high values in these three measures.

However, in the second expriment, the system was tested using the samples which have different fonts and sizes from training samples. When SEN or PR values are high (close to one or exactly one), it shows that system classifies almost all or exactly all digits correctly. It indicates the capability of the proposed method in Persian digits recognition.

We perform a comparison between our proposed method and methods introduced in other researches to show the high performance of our approach. The results of this comparison are shown in Table 5.

TABLE 2. AC and TFM values for two different experiments.

Experiments	TFM	AC
Experiment 1: samples with the same font and size of training data	0.9614	%98.05
Experiment 2: samples with different size and font from training dataset	0.9610	%98

TABLE 3. The obtained accuracy for each digit by applying the proposed method

Numerals	AC (%)
Zero	100
One	97.7
Two	92.2
Three	98.3
Four	98.8
Five	100
Six	100
Seven	96.6
Eight	99.4
Nine	99.4

According to the results, the proposed method require a small training set, recognizes both Normal and Bold faces samples, and is persistent to font variancy. Also, results of the recognition by the proposed approach show a very good promise indeed, especially as compared to other neural network based systems. Accuracy rate is considerably high. We implemented the method introduced in Ref. [19] for recognizing Persian digits. The result is shown in Table 5 as well. The process of feature extraction is different.

TABLE 4. Measured values of PR, SEN and FM for each digit. First row shows values resulted from the first expriment and the second one shows values from the second expriment

	Zero	One	Two	Three	Four	Five	Six	Seven	Eight	Nine
PR	0.97	0.97	0.95	0.96	0.99	0.99	0.97	0.98	1	1
	1	0.90	1	1	1	1	1	1	0.90	1
SEN	1	0.97	0.92	0.98	0.98	1	1	0.96	0.99	0.99
	0.90	1	1	0.90	1	1	1	1	1	1
FM	0.98	0.97	0.93	0.97	0.98	0.99	0.98	0.96	0.99	0.99
	0.94	1	0.95	0.94	1	1	1	1	0.95	1

TABLE 5. Comparison of the proposed method with other previous researches in recognizing Persian digits

	Number of Test and training samples	Classification method	Persistent to fonts	Recognizing normal & bold	Accuracy (%)
EbrahimNezhad et al. [16]	216 tests - 216 trains	Fuzzy combination	✕	normal	97.5
Montazer et al. [17]	105 tests- 123 trains	Neuro fuzzy	✕	normal	95
Boveiri [14]	80 tests- 320 trains	Fuzzy min-max neural network	✕	normal	98.75
Samadiani and Hassanpour [19]	2000 tests- 20 trains	SOM neural network	✓	**Normal, bold**	97.1
Proposed method	2000 tests- 20 trains	SOM neural network	✓	**Normal, bold**	**98.05**

In recognizing English digits, after rotating the image in 45 degrees, it is divided into two parts in horizontal direction based on center of the image. In each part of the image, the total number of 1s in each of the rows and columns is calculated. While in recognition of Persian digits, the feature vector is extracted by counting number of 1s in each row and column. The time required to train and recognize SOM is faster compared to other ANN based systems because SOM does not have hidden layers and the propsed approach requires a small number of sample for training. It recognizes the patterns based on the network findings and has its own solution. It doesn't need to know the output for learning. It is an advantage and more efficient with pattern association.

4. CONCLUSION

In this study, a method has been represented to recognize digits in different fonts and sizes. The total accuracy of the proposed method is 98.05%. This accuracy has been obtained by a simple neural network with just a small data set. In this method, image of digits have been resized to 30x30 pixels images in the preprocessing step. Then, the features have been extracted by counting number of 1s in the rows and columns of each image, respectively. These features are similar for the same class of digits despite differences in fonts and sizes. In this paper, a SOM neural network equipped with Jensen similarity measure has been used to recognize and classify digits. The evaluation results prove that the proposed technique is able to recognize Persian digits with a high accuracy even with different fonts and sizes. Comparison results with other existing methods show that the proposed method has some unique advantages: requiring small training set, recognizing both Normal and Bold faces of digits, using a simple classification approach and being persistent to font variant.

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Self-organizing Map

چکیده

در این مقاله روشی جهت شناسایی مستقل از فونت و سایز ارقام چاپی فارسی توسط شبکه عصبی ارائه شده است. برخلاف روش ارائه شده این مقاله، روش‌های موجود مبتنی بر شبکه عصبی، تنها قادر به شناسایی فونتهای آموزش دیده شده هستند. هر ساله فونتهای جدیدی به عموم معرفی می‌شود که این فونت‌ها نمی‌توانند به درستی توسط سیستم‌های تشخیص الکترونیکی حروف شناسایی شوند. بنابراین، سیستم‌های موجود نیازمند بازآموزش برای به‌روزرسانی الگوریتم خود هستند. در این مقاله، روشی جهت شناسایی ارقام چاپی با دقت بالا توسط شبکه عصبی نگاشت خود سازمانده مجهز به ویژگی‌های مناسب ارائه داده‌ایم. برای ارزیابی کارایی روش، دو آزمون طراحی شده است. در آزمون اول، داده‌های مربوط به پایگاه داده‌ای با ۲۰۰۰ نمونه ارقام چاپی فارسی حاوی ۱۲ فونت و ۱۰ سایز مختلف را دسته بندی نموده و به دقت ۹۸/۰۵%رسیده‌ایم. در آزمون دوم روش ارائه شده برای شناسایی داده‌های دیده نشده با فونت و سایز متفاوت از مجموعه آموزشی استفاده شده است. نتایج دقت ۹۸% برای شناسایی داده‌های دیده نشده را نشان می‌دهد.

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