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Transformation-Invariant Classification of Persian Printed Digits

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Abstract

Optical character recognition is one of the most active branches of pattern recognition deals with different aspects of automatic recognition of written patterns. Among numerous techniques, systems, and software reported in the literature, Persian printed digits classification has not been attended a lot. In this paper, a consistent system for transformation-independent recognition of Persian printed numerals based on Hu moment invariants, which are invariant to translation, rotation, and scale has been introduced. Since utilization of these invariants tackles with some important issues such as noise sensitivity, compactness and invariance to reversal patterns, some operations to compensate these drawbacks have been done. In addition, a robust classifier named fuzzy min-max neural network has been used to encounter such a compact and overlapped feature space. Set of different experiments has been done and results show the proposed system is so successful to invariant classification of Persian printed digits.

Keywords: *Fuzzy min-max neural network, moment invariants, optical character recognition, Persian printed digits classification.*

1. Introduction

Optical character recognition (OCR) is one of the active branches of pattern recognition, deals with different aspects of automatic recognition of written patterns. OCR system is an image processing system which gets a textural image as input and after processing, it produces corresponding editable text as output. Digits classification/recognition is subset of OCR, which has a large number of applications in license plate recognition, automatic check ordering in banks, automatic postal code recognition of mails, processing of numeral forms etc.

Fig. 1 shows the Persian digits. With respect to similarity of "two," "four," and "six" and shape reversal of "seven" and "eight" related to each other, Persian numeral characters classification is so complicated. Regarding to importance and extensive application, many researches [1]-[13] have been done in the field of Persian numeral character classification/recognition and some data-sets [14]-[16] have been introduced. Unfortunately, all of them are on handwritten digits and printed digits have not been attended a lot.

Among the few works on Persian machine-print digit recognition reported in the literature, Ebrahimnezhad et al. [17] presented a fuzzy approach based on using entropy function to improve fuzzifier function definition for Persian digit recognition irrespective of font and size. Box method was used to generate the feature vector. The system tested by various fonts and finally achieved 97.5% correct recognition. In [18] they extended their system. They presented a synthesis approach that uses three fuzzifier functions simultaneously, and with post processing using another fuzzy system, they reported complete correct recognition;

However, character "zero" was neglected in their experiments and the utilized data set is unknown as well. The author [19] proposed a system for Persian printed numeral characters recognition using geometrical central moments to generate the feature vector and fuzzy min-max neural network as classifier. The system tested on a data set encompassing various samples and finally 99.16% correct recognition was achieved. The most drawback of the system was the method of feature extraction which is sensitive to rotation, so an extra skew correction step is necessary to compensate this shortcoming.

Moments invariants are a set of nonlinear functions, which are invariant under translation, rotation, and scale. Hu [20] first introduced them as feature for visual pattern recognition. These moments are used a lot as image descriptor in the field of OCR systems and the author demonstrates efficiency of them in Persian printed character recognition.

Artificial neural network (ANN) has been inspired from biological neural structure of human brain and has the extensive power in pattern classification and clustering. Fuzzy logic is a consistent logic to encounter ambiguity and uncertainty. In fuzzy logic, a predicate is not necessarily true or false and it can be relatively true and false regarding to condition. Aggregation of neural networks and fuzzy logic generates a new heuristic tool so-called fuzzy-neural network (FNN) which has a lot of potential power to solve problems related to human intelligence [21]. In an OCR system, FNN seems to be so adequate; neural network recognizes characters while fuzzy logic can help it to encounter ambiguity. These ambiguities may arise from image noise, undesirable connections, character similarities etc.

Simpson first introduced fuzzy min-max neural network for pattern classification and clustering [22], [23]. Properties like no needs to adjust the fuzzy sets by expert person, online adaptation, nonlinear separability, high ability to encounter the overlapping classes, short training time, existence of parameters for better adaptation to input data and successful results in Persian printed letters recognition in [24] and Persian printed numeral character recognition in [19] are good reasons to use this kind of FNN in this paper.

The remainder of paper is organized as follow. In the next section, structure of proposed system is described. Section III surveys preprocessing stage. Section IV gives detail description of moment invariants and feature vector enrichment in representation stage. In section V, fuzzy min-max neural network and its properties are introduced. Section VI reports the experimental results. Finally, the conclusions are outlined in section VII.

Zero	One	Two	Three	Four
۰	۱	۲	۳	۴
Five	Six	Seven	Eight	Nine
۵	۶	۷	۸	۹

Fig. 1. A typical Persian machine-printed numerical characters.

2. The Proposed System

Fig. 2 shows the structure of the proposed system. Just like every classical image processing system [25], the proposed system composed of several isolated processing stages. In preprocessing stage, noise reduction is done to enhance the input image. In representation stage, moment invariants are used as image descriptor. Also in this stage, feature vector is enriched using an extra statistical feature. In the last stage, extracted features are fed into a fuzzy min-max neural network and digits are classified.

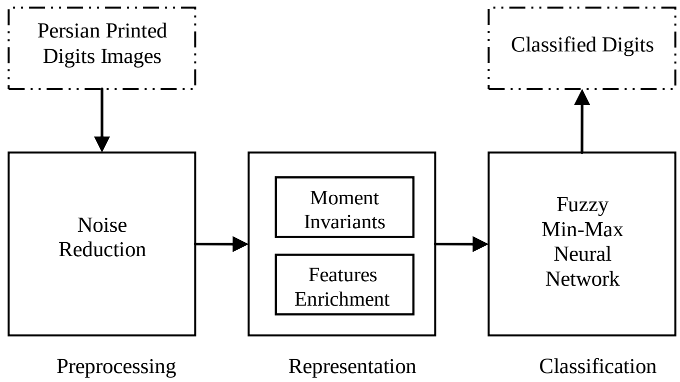

Fig. 2. Structure of the proposed system.

3. Preprocessing

Moment invariants are sensitive to noise [26]. Thus in this stage, noise reduction is done to compensate this defect. A nonlinear median filter using a 3×3 mask has been used for image noise reduction. This filter has high ability to noise removal, retains sharp edges, and fixes some undesired disconnections if possible [25].

4. Presentation

Moment invariants have been used as character image descriptor. These moments are nonlinear, invariant under translation, rotation, scale, and image reversal. With regard to reversal shape of Persian "seven" and "eight" related to each other, moment invariants cannot discriminate them. Therefore, feature vector is enriched using an extra statistical feature, that is, count of upper half of image pixels divide by count of lower half of image pixels. Since these two digits have triangular shape, the aforementioned statistical feature can definitely discriminate them.

4.1. Moment Invariants

Geometrical moment of order ($p+ q$) for a *two*-dimensional discrete function like image is computed using (1). If the image can have nonzero values only in the finite part of *xy* plane; then moments of all orders exist for it [20].

$$m_{pq} = \sum_{x=0}^{M-1}\sum_{y=0}^{N-1} x^p y^q f(x,y) \tag{1}$$

where $f(x, y)$ is image function and M, N are image dimensions. Then, geometrical central moments of order ($p+ q$) can be computed using (2).

$$\mu_{pq} = \sum_{x=0}^{M-1}\sum_{y=0}^{N-1} (x-\bar{x})^p (y-\bar{y})^q f(x,y) \tag{2}$$

where $\bar{x}$ and $\bar{y}$ are gravity center of image and are calculated by (3). Actually with image translation to coordinate origin while computing central moments, they become translation invariant.

$$\bar{x} = \frac{m_{10}}{m_{00}} \quad , \qquad \bar{y} = \frac{m_{01}}{m_{00}} \tag{3}$$

Note that in a binary image, m_{00} is count of foreground pixels and has direct relation to image scale, therefore central moments can become scale normalized using (4).

$$\eta_{pq} = \frac{\mu_{pq}}{m_{00}^{a}} \quad , \quad a = \frac{p+q}{2} + 1 \tag{4}$$

Having normalized geometrical central moments up to the order three, seven-moment invariants introduced by Hu [20] can be computed by using (5).

$$\begin{aligned}
\varphi_1 &= \eta_{20} + \eta_{02} \\
\varphi_2 &= (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2 \\
\varphi_3 &= (\eta_{30} - 3\eta_{12}) + (3\eta_{21} - \eta_{03})^2 \\
\varphi_4 &= (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2 \\
\varphi_5 &= (\eta_{30} - 3\eta_{12})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] \\
&\quad + (3\eta_{12} - \eta_{03})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] \\
\varphi_6 &= (\eta_{20} - \eta_{02})[(\eta_{30} + v_{12})^2 - (\eta_{21} + \eta_{03})^2] \\
&\quad + 4\eta_{11}(\eta_{30} + \eta_{12})(\eta_{21} + \eta_{03}) \\
\varphi_7 &= (3\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] \\
&\quad + 3(\eta_{21} - \eta_{03})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2]
\end{aligned} \tag{5}$$

Table I lists moment invariants (φ_1-φ_7) for different status of character in fig. 6 after preprocessing where μ and σ are sample mean and sample standard deviation respectively and σ/μ % is percentage of spread of moment Invariants values from their corresponding means. The small values of σ/μ %'s row indicate that invariant moments have little tolerance under transformations like translation, rotation, and scale. Note that because of wide range of these moments, logarithms of their magnitudes have been used as feature.

TABLE I. MOMENT INVARIANTS FOR DIFFERENT STATUS OF CHARACTER IN FIG. 6 AFTER PREPROCESSING.

	φ_1	φ_2	φ_3	φ_4	φ_5	φ_6	φ_7
Fig. 6a	-1.24	-4.03	-3.76	-5.59	-10.7	-8.00	-9.47
Fig. 6b	-1.31	-4.42	-3.99	-5.88	-11.1	-8.51	-11.3
Fig. 6c	-1.24	-4.03	-3.76	-5.59	-10.7	-8.00	-9.47
Fig. 6d	-1.24	-3.88	-3.88	-5.74	-10.9	-7.94	-9.79
μ	-1.26	-4.09	-3.85	-5.70	-10.8	-8.11	-10.0
σ	0.035	0.231	0.111	0.140	0.161	0.267	0.862
σ/μ %	2.782	5.658	2.888	2.469	1.485	3.294	8.618

4.2. Feature Vector Enrichment

Persian "seven" and "eight" are vertically reverse of each other. With respect to invariance of moment invariants under image reversal, they cannot discriminate these characters. Thus, feature vector is enriched using an extra statistical feature, that is, count of upper half of image pixels divide by count of lower half of image pixels. Both Persian "seven" and "eight" have triangle shape and are reverse of each other, so relation of their upper half of image pixels to lower half of image pixels is completely different [19]. It has also been shown in fig. 3.

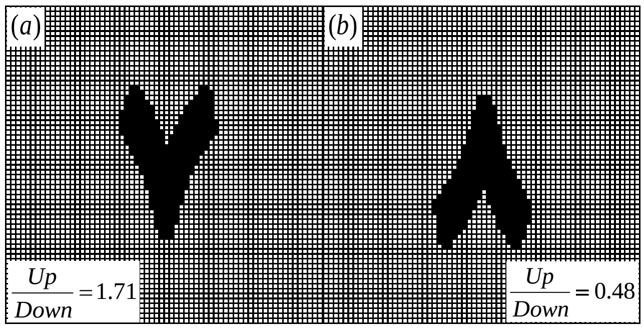

Fig. 3. (a) Persian "seven" digit (b) Persian "eight" digit. With computed extra feature for them [19].

5. Classification Using Fuzzy Min-Max Neural Network

In this paper, fuzzy min-max neural network (FMMNN) [22] has been used to classify Persian printed digits. FMMNN works based on generating and utilizing hyperbox fuzzy sets. A hyperbox defines a region of the *n*-dimensional pattern space that has patterns with full class membership. A hyperbox is completely defined by its min point and its max point, and a membership function is defined with respect to these hyperbox min-max points. An illustration of the min and max points in a *three*-dimensional hyperbox has been shown in Fig. 4. Membership function of each hyperbox gives membership value of the input patterns relative to that hyperbox. Patterns that are near of the hyperbox get high membership values and others which are far from the hyperbox, get the lower ones.

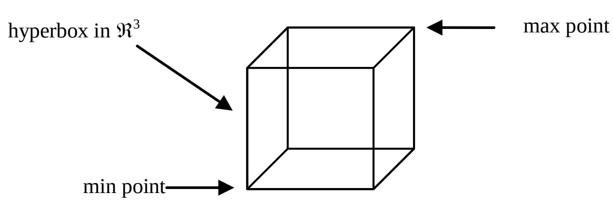

Fig. 4. The min-max *three*-dimensional hyperbox [22].

FMMNN by cooperation of membership functions of the all hyperboxes determine membership value of each input pattern for each class classifies them. Proper adjusting of size and location of each hyperbox in the pattern space do training in FMMNN. Fig. 5 illustrates separation of two classes by *two*-dimensional hyperboxes.

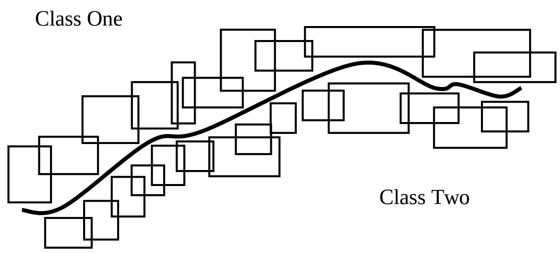

Fig. 5. Separation of two different classes by *two*-dimensional hyperboxes [22].

5.1. FMMNN Properties

Some properties of FMMNN which are good reasons to select this kind of FMM in this paper are presented as follows.

- *Online Adaptation:* FMMNN is able to learn new classes and refine existing classes quickly and without destroying old class information or need to retrain them.
- *Nonlinear Separability:* FMMNN is able to make decision regions that separate classes of any shape and size.
- *Overlapping Classes:* It has ability to form a decision boundary that minimizes the amount of misclassification for all of the overlapping classes.
- *Training Time:* one of the excellent properties of FMMNN is the short training time as in most cases it needs only one pass for training.
- *Tuning Parameters:* FMMNN has parameters for better adaptation with input patterns. θ parameter is a user defined value that bounds the maximum size of hyperboxes during the FMMNN training. Lower values of θ make more (and smaller) hyperboxes that seem to be proper for separating nonlinear, ambiguity, and overlapping classes. Although some of these hyperboxes are not necessary increasing training and classification time. γ parameter is also a user defined value so-called sensitivity parameter and regulates how fast the membership values decrease as the distance between input pattern and hyperbox increases. In all experiments, it is considered $\theta = 0.1$ and $\gamma = 1.0$ unless where it is expressed explicitly.

6. Implementation and Experimental Results

The proposed system was implemented on a Penitum4 (2.6GHz) desktop computer with Microsoft Windows XP (SP2) platform using Microsoft Visual Basic 6.0 programming language. Required time to compute seven moment invariants (without preprocessing stage) from a typical 64×64 character image was 62 ms (mean of 10 times of algorithm execution was used).

6.1. The Utilized Data Set

The data-set introduced in [19] has been used. This data-set consists of 64×64 binary images of all 10 Persian numeral characters in four groups. The first group was regular characters with same size and without any translations and rotations. The second group was rotated characters in the range of (-45, 45) degree. The third group was randomly translated characters and finally characters of the fourth group had various sizes. There were 10 samples for each character in each group, that is, those were totally 400 samples (40 samples per character). Fig. 6 shows a sample image of each group of Persian "three" in the data-set. In all experiments, half of samples have been used to train and the remainders as test data unless where it is expressed explicitly.

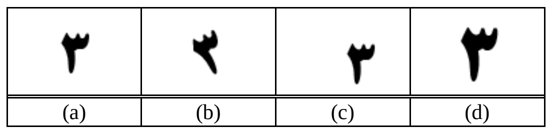

Fig. 6. A sample image of each group of Persian digit "three" in the dataset. (a) Regular (b) Rotated (c) Translated (d) Scaled [19].

6.2. Experiment without any Feature Vector Enrichments

In the first experiment, feature vector enrichment was not been used, that is, feature vector consists of only seven moment invariants. 136 hyperboxes were generated during the FMMNN training and finally 90% of samples were classified correctly. Table II shows the confusion matrix of this experiment. It is clear that most errors were occurred because of shape reversal of "seven" and "eight" related to each other.

TABLE II. CONFUSION MATRIX OF EXPERIMENT USING SEVEN MOMENT INVARIANTS AS FEATURE VECTOR WITHOUT ANY ENRICHMENTS.

	۰	۱	۲	۳	۴	۵	۶	۷	۸	۹
۰	19							1		
۱		19					1			
۲			19	1						
۳				20						
۴			1		19					
۵						20				
۶					1		19			
۷								16	4	
۸						1		10	9	
۹										20

6.3. Experiment with Feature Vector Enrichment

In the second experiment, feature vector is enriched using the extra feature. 161 hyperboxes were generated during the FMMNN training and finally 94% of samples were classified correctly. In the next experiments, the extra feature has been added multiple times in the feature vector redundantly to increase its effect. Fig. 7 illustrates results of these experiments. The results (98%) were not improved by adding the extra feature more than two times into the feature vector, so it seems to be the best number to add the extra feature into the feature vector. Table III shows the corresponding confusion matrix. Feature vector enrichment seems to have good effect to enhance correct classification of "seven" and "eight" as we expected.

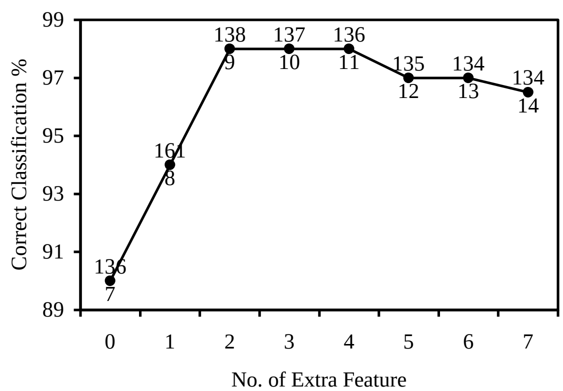

Fig. 7 Correct classification diagram with respect to adding the extra feature several times to the feature vector. The numbers under diagram are size of utilized feature vector and the above ones present count of the

TABLE III . CONFUSION MATRIX OF EXPERIMENT USING SEVEN MOMENT INVARIANTS AS FEATURE VECTOR WITH TWO TIMES ENRICHMENT.

	۰	۱	۲	۳	۴	۵	۶	۷	۸	۹
۰	19							1		
۱		20								
۲			20							
۳				20						
۴					20					
۵						20				
۶					1		19			
۷								20		
۸						1			19	
۹		1								19

6.4. Fuzzy Min-Max Neural Network Parameters

Fig. 8 illustrates correct classification diagram with respect to different values of θ parameter (maximum size of the hyperboxes). The numbers above the diagram present count of generated hyperboxes during FMMNN training which increase as the value of θ decreases. The results (98.5%) were not improved using values less than "0.08" which seems to be the best value for this parameter.

Fig. 9 illustrates correct classification diagram with respect to different values of γ parameter (sensitivity parameter). The results (98.5%) was not improved using values less than "1" which seems to be the best value for this parameter (decreasing this parameter increases the hyperboxes sensitivity).

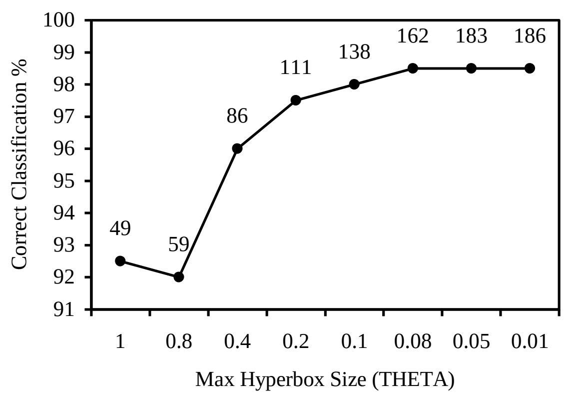

Fig. 8. Correct classification diagram with respect to different values of θ parameter (maximum size of hyperboxes). The numbers above the diagram present count of the generated hyperboxes during FMMNN training which increase as the value of θ decreases.

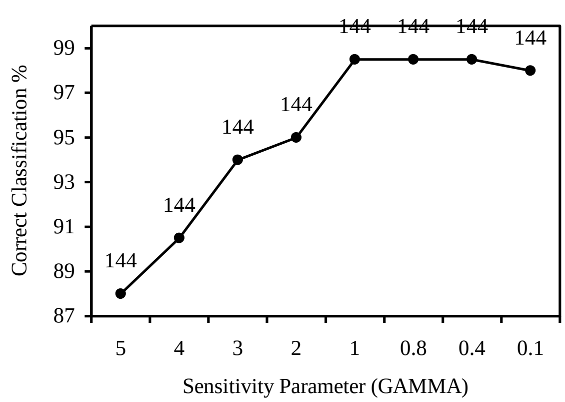

Fig. 9. Correct classification diagram with respect to different values of γ parameter (sensitivity parameter). The numbers above the diagram present count of the generated hyperboxes during FMMNN training.

6.5. Effect of Size of Training Samples

Fig. 10 illustrates correct classification diagram with respect to different values of training samples. With greater values of this parameter, more hyperboxes have been generated as we expected. In each experiment, reminder samples were used as test samples. The best result (98.75%) was achieved using 80% of samples for training and the remainder 20% for testing.

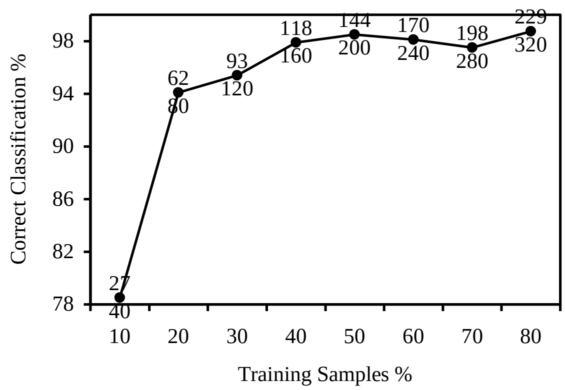

Fig. 10. Correct classification diagram with respect to different values of training samples. The above numbers of diagram present count of the generated hyperboxes during FMMNN training and the under ones are number of training samples.

7. Conclusions

A new proposed system for transformation-invariant classification of Persian printed digits was introduced. In the representation stage, moment invariants were used as image descriptor. Whereas these moment invariants are invariant under image reversal, thus feature vector was enriched using an extra statistical feature to discriminate the characters like "seven" and "eight." In the classification stage, a fuzzy min-max neural network was used as digits images classifier. Set of different experiments was done and various results were achieved. Finally, the best result was 98.75% correct classification that showed moment invariants with fuzzy min-max neural network are adequate to invariant Persian printed digits classification.

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