The presentation of a new method resulted from patterns overlapping for handwritten Farsi digits recognition

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Abstract

Making a useful model to recognize handwritten text always has been important for researchers. In the facing research, Farsi handwritten digits which are available in the Hoda dataset, which is a proof for researchers, have been investigated. This method consists of thinning of digits, selecting a number of fixed pixels with equal interval (converting digit to points) on each sample and at last overlapping of all samples which are in one class. The purpose of this research is creating a reference pattern for each digit. In order to recognize the related class of the new sample only we need to put the sample on al ten references to specify the new sample. The results signify a high performance of the method.

Key words: handwritten Farsi digits, referee pattern, overlapping, dataset, thinning.

1. Introduction

Recognition of handwritten letters and digits has been always one of the interesting subjects for research. Many works have been also done on recognition of Persian and Arabic handwritten letters and digits. In the research conducted by Darvish et al. (2006), shape matching algorithm has been used for recognition of Persian handwritten digits. For each point sampled on the contour of a shape, a descriptor is achieved based on spatial distribution of other points of the connector. In another research, Parvin et al. (2008) have suggested a method for improvement of the recognition system's operation. The main idea of the method suggested by them is the use of binary classifiers. In another research, Alizadeh et al. (2008) have presented a method based upon genetic algorithm for formation of a neural network group using a weighted classifier selection method based on vote. The research conducted by

Shahabi and Rahmati (2009) has made use of Gabor filter bank proper for the structure of Persian handwritten texts and visual system. In another work by Mr. Parvin et al. (2009), binary classifiers have been used for reinforcing this group of classifiers. Due to its higher accuracy, this group can decrease the rate of error in feature space. In a research, moment features and Bayes' classifier have been used for recognition of Persian handwritten letters (Azmi. 1994). Masroori and Pour-khmene (1988) has made use of dynamic time wrapping algorithm for recognition of digits. What we have done has been based upon shape matching and overlaying learnable samples in order to make reference patterns. In this method, every image has been described by 20 points gathered in the middle of black pixels with equal distances from each other. Our method is based on form matching and includes 3 steps:

1- preprocessing and extraction of 20 points
2- Overlaying training samples on each other and making patterns of each class
3- recognition of testing samples

In the second part, two steps of preprocessing which are very important have been applied on the samples. In the third part, patterns creation method for each class and the method of recognizing the class related to experimental samples have been discussed. In the forth part, we have compared the suggested method with other methods in regard to the rate of recognizing the digits. The results of this part indicate appropriateness of the suggested method.

2. Preprocessing Step

The preprocessing step includes the three stages of equalizing digits' size, thinning and transformation of the thinned image into dots. Equalization has been done by transformation of all digits into 44 rows and 34 columns of pixels and the two other stages would be mentioned later (kheir-khah and rahmanian 2007).

2.1. Thinning

In this phase, canny algorithm has been used for thinning and reaching the skeleton of each digit without any erosion or disconnection. This algorithm reaches a proper structure which maintains the original shape of the digit and does not make fake data. Figure 1 is an instance of this phase's output. The output in this phase is only a continuous skeleton transformed into the standard size 44x34. The purpose of this phase is to remove the problem due to difference in thickness of handwritten digits.

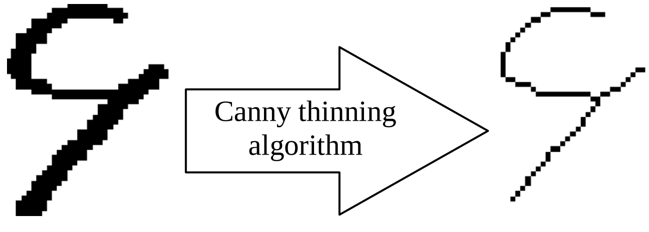

Fig 1: thinned sample

2.2. Transformation of Digit to Dots

In this part of preprocessing, the thinned digit has been transformed into an image constituted of only 20 black pixels. The major advantage of this method is its resistance to little changes, simplicity of implementation and its high accuracy in recognition. Hence, a more accurate description of the thinned image can be presented. Moreover, by this method a kind of differentiation can be made between different digits. What is evident is that the maximum error in recognition of handwritten digits is related to the digits 2 and 3. Therefore, according to the wider space of digit 3, the distance between its black pixels is more in comparison to digit 2. As a result, the rate of recognition of handwritten digits can be increased.

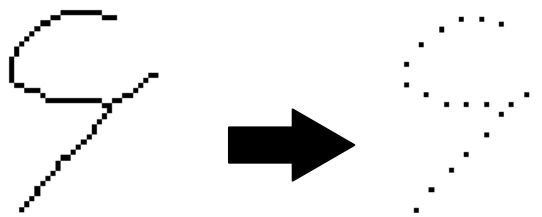

Fig 2: transformation of thinned image into dots

3. Recognition of Persian handwritten digits

The dataset, on which we have applied recognition of digits, is a set including 1500 Persian handwritten digits written by different persons and collected in data base.

3.1. Recognition of Representatives of each Class

Representatives of each class are of importance since they are considered as the reference pattern for recognition of the digits of the experimental set. Therefore, correct selection of these representatives is one of the most important stages in recognition of handwritten digits.
In this stage, by inputting all digits of each class on each other we reach matrixes that can be used as the patterns of the related class. We will have the following criterion for the *i*th class.

$$D_i(x,y) = \sum_{n=1}^{100}\sum_{x=1}^{44}\sum_{y=1}^{34}(F_n(x,y) * (-1) + 1) \qquad (1)$$

$F_n(x,y)$: value of the *n*th sample in row x and column y which is zero or one
$D_i(x,y)$: the pattern obtained for the *i*th class

Samples of all classes have been stored in 44×34 dimensions. We expect an increase in the number of rows and columns for each black pixel in the *n*th sample. By this method, we would reach a pattern for each class using all experimental samples of that class. Reference pattern related to digit "۹" is seen in figure 3. (Khosravi and Kabir. 2007)

Fig 3: reference pattern for digit “9”

3.2. Patterns' Accreditation

Now we look for a criterion for recognition of the validity of the pattern of each class. Therefore, we have to find the rate of recognition of the samples constituting each class by the related pattern. In order to recognize the level of similarity of each sample to the *i*th class, we act as follow:

$$s_i = \begin{cases} \sum_{x=1}^{44}\sum_{y=1}^{34} D_i(x,y) & , \quad \text{if } (F_n(x,y) == 0) \\ s_i - \text{negative\_grant} & , \quad \text{else} \end{cases} \tag{2}$$

S_i: rate of similarity of the *i*th class's pattern to the *n*th sample
Negative_grant: the negative point resulted from placement of the sample black pixel in an invalid place
Zero indicates black pixel and one indicates dead pixel.
By the criterion above, allocation of each sample to the related class has been determined and hence the recognition rate of each pattern is calculated.

3.3. Creating New Patterns

Having one reference for each class, correct recognition rate for training samples is equal to 77 percent. In order to increase the recognition rate, it would be necessary to consider other patterns for each class. To do so, the samples of each class not recognized correctly have been used for creating new patterns for the related class.
We continue this process for each class and its samples till the rate of non-recognition of the patterns of the considered class is less than 4%. The number of the patterns obtained for each class has been presented in table 1

Number of reference pattern	Slightly digit
2	0
3	1
2	2

3	3
3	4
4	5
4	6
2	7
2	8
2	9

Table 1. Number of pattern in various classes

3.4. Recognition on the Entire Set of Digits

Having extracted the reference patterns for each class as described in the previous parts, recognition has been applied on the entire set of experimental digits. The recognition rate of this experiment is 91.33%. The recognition rate of each digit has been presented in table 2.

Recognition rate (in percent)	Slightly digit
98	0
98	1
84	2
88	3
90	4
96	5
86	6
94	7
92	8
92	9

Table 2. Correct recognition for each digit

4. Conclusion

In the present article, a pattern matching algorithm has been used. After several stages of preprocessing, a series of patterns has been obtained (for each class) by inputting the experimental samples on each other. Afterwards, we make use of the samples not recognized correctly in order to add new patterns to the classes' patterns.

The most important preprocessing step is related to extraction of 20 light pixels out of each handwritten digit and causes elimination of some noises from digits and differentiation between digits like 2 and 3.

In this experiment conducted on 1500 digits written by different persons, 91.8% of recognitions were correct. Besides, 1000 digits have been used for education (creating pattern) and 500 digits have been used for experiment. But using some preprocessing techniques such as skew correction, the visual quality of digits can be improved or separate digits like 0 or 1 from other digits before the main recognition. Thus, correct recognition is improvable.

References

Alizadeh, H., Parvin, H., Minaei-Bidgoli, B. (2008), A New Approach to Improve the Vote-Based Classifier Selection", *Fourth International Conference on Networked Computing and Advanced Information Management*, Iran.

Azmi, R., & Kabir, E. (1984). Recognition of handwritten Farsi Letters, *2th Conference of power engineering*, iran, pp.277-285.

Darvish, A. R., & Kabir, E., & Khosravi, H. (2006). Application of shape adaptation in Recognition of Handwritten Farsi Digits, *journal of technical & engineering modarres*, Vol. 22, pp. 37-47.

Kheir-khah, A. R., & Rahmanian, E. (2007). System of Recognition of Handwritten Farsi Digits based on active training algorithm using committee of classifiers, *First Joint Congress on Fuzzy and Intelligent Systems*, Ferdowsi University of Mashhad, Iran, 29-31 Aug 2007

Khosravi, H., & Kabir E., (2007), Introducing a very large dataset of handwritten Farsi digits and a study on their varieties, *Pattern Recognition Letters*, Vol. 28, No. 10, pp. 1133-1141**.**

Masrouri, K., & Pour-mohseni khamene, V. (1988). Recognition of handwritten digits using DTW algorithm, *4th annual International Conference of computer institution of iran*, pp. 1-7.

Parvin, H., Alizadeh, H., Minaei-Bidgoli, B., & Analoui, M., (2009), A Scalable Method for Improving the Performance of Classifiers in Multiclass Applications by Pairwise Classifiers and GA, *Fourth International Conference on Networked Computing and Advanced Information Management*, Iran.

Parvin, H., Alizadeh, H., Moshki, M., Minaei-Bidgoli, B., & Mozayani, N., (2008); Divide & Conquer Classification and Optimization by Genetic Algorithm, *Third International Conference on Convergence and Hybrid Information Technology*, Iran.

Shahabi F. & Rahmati, M. (2009), A New Method for Writer Identification of Handwritten Farsi Documents, *10th International Conference on Document Analysis and Recognition*, Iran.