MVA2005 IAPR Conference on Machine VIsion Applications, May 16-18, 2005 Tsukuba Science City, Japan
6-4

A Hybrid Structural/Statistical Classifier for Handwritten Farsi/Arabic Numeral Recognition

Saeed Mozaffari [1,2]
[1] Electrical and Computer Departement
Qazvin Azad University,Iran
S_mozaffari@aut.ac.ir

Karim faez [2]
[2] Electrical Engineerig Department, AmirKabir University of Technology, Tehran, Iran
k_faez@aut.ac.ir

Majid Ziaratban [2]
[2] Electrical Engineering Department, AmirKabir University of Technology, Tehran, Iran
m_ziaratban@aut.ac.ir

Abstract

In this paper a new Farsi/Arabic numeral recognition system, based on the combination of structural and statistical classifiers, is presented.

The structural method cannot deal with broken characters well. A statistical classifier would be more suitable for these unconnected samples. Thanks to the combination of structural and statistical approaches, a complete description of the characters can be achieved thus providing significant improvements in classification performance.

The recognition system has been tested on a database which includes 480 samples per digit (total of 6080). We used 280 samples of each digit for training and the rest (200) for test.

According to experimental results, classification rate of 97.31% is achieved for numerals on the test sets.

1 Introduction

The recognition of handwritten numerals is a challenging problem in pattern recognition. This is due to large diversity of writing styles and image quality. Pattern recognition systems typically involve two steps: *feature extraction* in which appropriate representation of patterns are developed and *classification* in which decision rules for separating pattern classes are defined. There are indeed as many possible features as the ways characters are written [1]. These features can be classified into two major categories: statistical and structural features. In the *statistical* approaches, the input pattern is characterized by a set of N features and its description is achieved by means of a feature vector belonging to an N-dimensional space. On the other hand, in *structural* approaches it is assumed that the pattern to be recognized can be decomposed into simpler components (called primitives) and then described in terms of simple appropriate attributes of primitives and their topological relations. In the field of handwritten character recognition, it is now agreed that a single feature extraction method and a single classification algorithm cannot yield a very low error rate [2]. Due to large variety of available feature extraction methods, many researchers have turned towards the use of several feature extractors. In [3] and [4] some combinational feature vector based on structural and statistical features was introduced. On the other hand, some researchers used more complex structures of classification, such as multistage classification schemes [5] or parallel combination of multiple classifiers [6].

Some previous works on recognition of isolated characters, words and scripts of Farsi and Arabic language have used structural features [7] [8], moment features [9] wavelet features [10] and fractal features [11]. Neural Networks [10][11] Hidden Markov Models (HMM) [8] and support vector machine (SVM) have been used as classifiers in these systems [12]. In this paper a new Farsi/Arabic numeral recognition system, based on the combination of structural and statistical classifiers, is presented. We used one structural and two statistical methods which are fractal and wavelet nearest neighbor classifiers.

The paper is organized as follows. In Section 2 the preprocessing and thinning algorithms are described. Section 3 presents the structural feature extraction method and Section 4 presents the statistical feature extraction method. The recognition algorithm is presented in Section 5. The experimental results are provided in section 6, and a conclusion is given in Section 7.

2 Preprocessing and Thinning

In preprocessing stage we smooth an input image to eliminate small holes and fill gaps in contours. An alternative way for smoothing is to use mathematical morphology. We applied closing transformation with masks S_1 and S_2 to smooth the input image.

$$S_1 = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}, \quad S_2 = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

We need some other preprocessing tasks for statistical methods. Since fractal and wavelet codes are sensitive to translation, scaling and rotation, the bounding rectangle of each character is found and scaled to a 64×64 pixel image. We used skeletonization approach outlined in [13] to make the system independent of stroke width.

3 Structural Feature Extraction

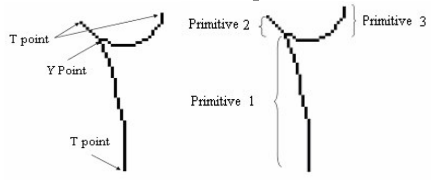
In structural feature extraction method, the image is first smoothed and its skeleton is obtained using a thinning algorithm. For skeleton decomposition, three feature points are introduced to characterize the convex/concave changes of a curve. These feature points were defined as follows:

1-"T" point: is a point which has only one black pixel in its 8-neighbors.

2-"Y" point: is an intersection point which has only three black pixels in its 8-neighbors.

3-"X" point: is an intersection point which has only four black pixels in its 8-neighbors.

Based on these feature points, the skeleton is decomposed into primitives. A primitive is defined as the skeleton segment which starts from a feature point and ends at a feature point. Fig.1 shows the skeleton, primitives and its feature points.



(a) (b)

Fig.1. Decomposition of a character:
(a) Feature points. (b) Primitives

A *primitive code* is derived for each primitive, which consists of 8 elements. Each primitive is divided into two equal parts. The algorithm traces each part and records changes in X and Y directions. Then the average and variance of X and Y variations are obtained. By repeating this procedure for the next primitive part, 8 elements ($p_1, p_2, ..., p_8$) can then be determined as follows:

p_1, p_2, p_3 and p_4 =Average and variance of X and Y changes in the first part.

p_5, p_6, p_7 and p_8 =Average and variance of X and Y changes in the second part.

In our approach, a one-dimensional vector named global code derived from the primitive codes is used to classify all handwritten numerals.For skeleton decomposition, we need to find the start point. The algorithm scans the image from left to right (along x axis) and from bottom to top (along y axis). The first (left-most) "T" point detected is taken as the start point.

After finding the start point, the algorithm traces the skeleton to find the next feature point. For "X" and "Y" feature points, the algorithm has different choices to trace the skeleton. By defining a priority such as chain codes, the algorithm can trace a primitive with higher priority. To trace all primitives in the skeleton, we need to save the coordinates of "X" and "Y" feature points. Since some of primitives in Farsi characters are symmetric, the average of X or Y variations will be near zero. To solve this problem, we divided each primitive into two equal parts and extracted primitive code for each part separately. Also some of characters can be written in different ways. To increase the accuracy of the algorithm, we divided each single primitive character into four equal parts. Then the coding algorithm is applied to each part separately and a primitive code with the length of 32 is obtained. Since the length of primitive codes vary for different characters (even for characters in the same class), the length of global codes will be variable. We will use these global codes as feature vectors in recognition stage. Fig .2 shows the primitive and global codes for a typical character.

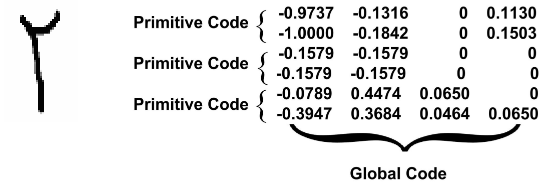


Fig 2. Left: a typical character with three primitives. Right: extracted primitive codes and global code

4 Statistical Feature Extraction

In this section two different statistical approaches which are fractal and wavelet methods will be described.

4.1 Fractal Feature

Fractal codes represent affine transformations which when iteratively applied to the range-domain pairs in an arbitrary initial image, the result is close to the given image. Each fractal code consists of six parameters such as corresponding domain coordinates for each range block, brightness offset and an affine transformation. Since characters and digits have simple images, we used the fixed size square blocks partitioning [14]. We used each fractal feature as a vector such that all images have a feature vector of the same size. In this method, the size of fractal features vector varies according to the size of range blocks. For an 64×64 image with N=16 (The size of range blocks) a feature vector with the length of 96 is obtained [11].

4.2 Wavelet Feature

For feature extraction with wavelet transform, since the characters images are not continuous, we used Haar wavelet which is also discrete. We applied the pyramid algorithm to each preprocessed image for decomposing it into 3 resolution levels. Then we used the approximation of images at level 3 and converted them into vectors by concatenating the columns, then we smoothed this vector with a low pass filter. In preprocessing stage, we scaled the image of each character into a 64×64 image, so the approximation of image at level three of pyramidal algorithm will be a 8×8 pixel image. This means that the length of our feature vectors is 64.

5 Recognition

For recognition, the idea of hybrid classifier is motivated by the fact that, ideally, the errors associated with each numeral would be independently distributed. This means when one of different classifiers makes an error, the other classifiers would be able to compensate and correct the error, with a high probability. But in reality, this did not occur and many of samples classified in error in one classifier were also incorrectly classified by other classifiers. Nevertheless, we still expect an improvement in recognition rate when combining the classifiers.

The structural method cannot deal with broken characters well. A statistical classifier would be more suitable for these unconnected samples. Thanks to the combination of structural and statistical approaches, a complete description of the characters can be achieved thus providing significant improvements in classification performance. Fig.3 shows the architecture of our system.

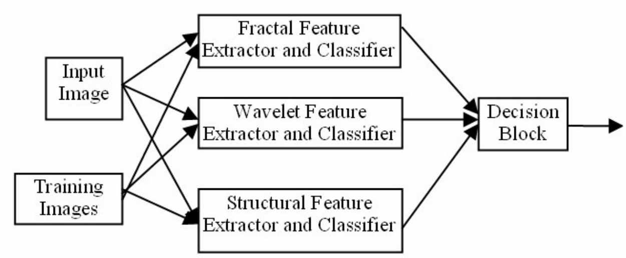


Fig.3. Architecture of our system

In Farsi language, there are ten digits that are shown in Fig.4.

0	1	2	3	4	5	6	7	8	9
۰	۱	۲	۳	۴	۵	۶	۷	۸	۹

Fig.4. Digits in Farsi and English

Because of the similarity between (۰و۵) and (۲و۳) especially in handwritten documents, 8 numerals are used in the postal codes in Iran. Since all classifiers in Fig.7 are nearest neighbor classifiers (NNC), we need a feature vector with the fixed size for each one.. The fractal and wavelet feature vectors which are obtained by feature extractors in section 4.1 and 4.2 have a fixed size with 96 and 64 components respectively. As mentioned in section 3, the obtained global codes don't have the same size. In our approach, principal component analysis (PCA) is performed on global codes to equalize the length of feature vectors for classification.

We can use these three classifiers in two different ways:

System I: In this system the decision block votes on the output of classifiers. It means when two out of three classifiers detected one class, that class is chosen.

Experimental results showed that structural classifier has the highest recognition rate. Moreover, its computational cost is generally negligible. On the other hand, statistical classifiers have a good performance on the misclassified patterns of the structural classifier. By combining two statistical classifiers (wavelet and fractal classifiers) only 30% of the errors can be compensated by the other classifier. When a hybrid structural/statistical classifier (structural and wavelet classifiers) is used, 90% of misclassified numerals by structural classifier can be assigned to the correct class by using statistical classifier. Based on this idea, the authors investigated the possibility of classifier performance improvement using system II.

System II: In this system, a validity parameter is defined to describe the reliability of the structural classifier as below:

For each input image, set initial validity parameter equal to 1. Neglect the assigned class and find the next candidate. If the current and previous classes were the same, increase the validity parameter. Continue this steps until the assigned classes were different. In this system we use wavelet classifier when validity parameter of the structural classifier was less than 7 for the input image. Fig.5 shows error rate of system II versus different values of validity parameters.

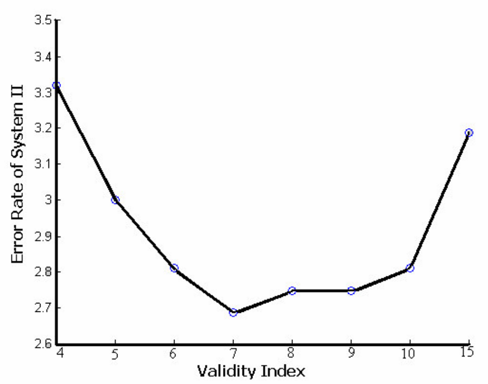


Fig 5. Error rate of system II versus different values of validity parameters.

6 Experimental Results

Training and test sets, were gathered from more than 200 people with different ages and different educational background. A total of 6080 handwritten numerals are used in the experiment, consisting of 480 samples per digit. Randomly selected 280 samples of each digit are used for training, and the remaining 200 samples of each numeral are used for testing. All experiments were performed on an Intel Pentium IV 2 GHz computer.By using the hybrid structural/statistical classifier, recognition rates of 100% and 97.31% are obtained for the training and test sets respectively. Table.1 shows these results.

Table.1. Performance comparison between various methods

Used feature	Feature extraction Time/Digit (Sec)	Recognition Time/Digit (Sec)	Recognition Rate
Structural	0.1	0.12	94.44%
Wavelet	0.1	0.08	90.6%
Fractal	2.5	0.1	88.2%
Hybrid System I	2.7	0.3	94.94%
Hybrid System II	0.2	0.18	97.31%

7 Conclusion

We demonstrate in this paper that high recognition rates can be achieved by combining structural and statistical classifiers. This is mainly due to the different description of a handwritten character by structural and statistical features which provides a good recognition rate.

As evident from Table.1, the proposed method leads to a sensible improvement of the classification rate in training and test sets. But some problems still remain: "How many classifiers and what kind of classifiers should be used? For each classifier, what types of features should be chosen?"

8. References

[1] V.K.Govindan and A.P.Shiraprasad ," Character Recognition-A review" Pattern Recognition, 23(7),pp.671-683,1990.

[2] Shridhar, M.Houle, G., Kimura, F." Handwritten word recognition using lexicon free and lexicon directed word recognition algorithms" Proc. 4th International Conference on Document Analysis and Recognition, Ulm,pp.861-865, 1997.

[3] L.Heutte, T.Paquet, J.V.Moreau, Y.Lecourtier and C.Olivier, " A Structural/Statistical feature based vector for handwritten character recognition" Pattern Recognition Letters 19,pp.629-641,1998.

[4] P.Foggia,C.Sansone,F.Tortorella and M.Vento" Combining statistical and structural approaches for handwritten character description" Image and Vison Computing 17,pp.701-711,1999.

[5] A.F.R.Rahman and M.C.Fairhurst," Introducing new multiple expert decision combination topologies: a case study using recognition of handwritten characters" Proc. 4th International Conference on Document Analysis and Recognition, Ulm,pp.886-891, 1997.

[6] L.Xu, A.Krzyzak and C.Y.Suen" Methods of combining multiple classifiers and their applications to handwritten recognition" IEEE Transaction on Systems, Man and Cybernetics 22 (3), pp.418-435,1992.

[7] I.S.I.Abuhiba, S.A.Mahmoud and R.G.Green "Recognition of handwritten cursive Arabic characters"

,IEEE Trans on Pattern Analysis and Machine Intelligence.Vol.16,No.6, June 1994,PP.664-672.

[8] M.Dehghan, K.Faez, M.Ahmadi and M.Shridhar "Off-Line unconstrained Farsi Handwritten Recognition Using Fuzzy Vector Quantization and hidden Markov Word Models".Proceeding of 15th International Conference on Pattern Recognition ,Vol.2,2000,pp.351-354.

[9] M.Dehghan and K.Faez,"Farsi Handwritten character Recognition with Moment Invarians", Proceeding of 13th International Conference on Digital Signal Processing, Vol.2, 1997,pp.507-510.

[10] A. Mowlaei, K. Faez and A. T. Haghighat, "Feature Extraction with Wavelet Transform for Recognition of Isolated Handwritten Farsi/Arabic Characters and Numerals", Proceedings of 14th International Conference on Digital Signal Processing, Vol. 2, July 2002, pp. 923-926

[11] S.Mozaffari, K.Faez and H.Rashidy Kanan": Recognition of Isolated Handwritten Farsi/Arabic Alphanumeric Using Fractal Codes" IEEE Proceeding of Southwest Symposium on Image Analysis and Interpretation. 2004,pp.104-108.

[12] S.Mozaffari, K.Faez and H.Rashidy Kanan" Feature Comparison between Fractal codes and Wavelet Transform in Handwritten Alphanumeric Recognition Using SVM Classifier" International Conference on Patter Recognition, pp. 331-334,2004.

[13] A.Rosenfeld and A.C.Kak, "Digital Picture Processing", Vol.2, pp.232-240, Academic Press,2nd Ed, 1982.

[14]- Ning Lu,: Fractal Imaging, Academic Press, June 1997.

[15] K.Fukunaga, " Introduction to statistical pattern recognition", 2nd ed, 1990.