Two Methods for Recognition of Hand Written Farsi Characters

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Abstract

Optical character recognition (OCR) is one of the active bases of sample detection topics. The current study focuses on automatic detection and recognition of hand written Farsi characters. For this purpose; we proposed two different methods based on neural networks and a special post processing approach to improve recognition rate of Farsi uppercase letters. In the first method, we extracted wavelet features from borders of character images and learned a neural network based these patterns. In the second method, we divided input characters into five groups according to the number of their components and used a set of appropriate moment features in each group and classified characters by the Bayesian rule. In a post-processing stage, some structural and statistical features were employed by a decision tree classifier to reduce the misrecognition rate. Our experimental results show suitable recognition rate for both methods.

Keywords: Optical Character Recognition, Hand Written Farsi Characters, Neural Networks, Wavelet Transform, Decision Tree.

1. INTRODUCTION

In today world, almost all of the information is kept and processed by computers. However, using paper and paper forms are common in collecting information yet. The collected information in paper form must be changed to computer information anyway. A simple way of that is employment of many employees besides high costs, low speed and lots of mistakes to enter these forms into computers directly. The better way is an efficient method that a machine can extract and save the information of forms automatically. This automatic method is called Optical Character Recognition (OCR).

The application of systems based on OCR have been common in many commercial and industrial places like hospitals, banks, post offices, insurance offices and journal publishers [1-6]. In these applications, use of optical character recognition has two suitable properties [7]. i) the speed of information access is increased because there is possibility of search and edit in contrast to pictures and ii) the required space for information saving is decreased because texts files that extracted from pictures are usually take less space than picture files.

Totally, OCR systems are categorized into two domains [8]. One focuses on picture detection of letters after entrance to system (by scanner or digital camera) that is called offline recognition. In the other domain however, the writer enters the texts directly to system (by an optical pen) that is called online recognition. Online detection is easier than offline method because of some additional properties such as pen motion, the pen pressure and etc [9]. So in this study, we concentrate on hand written characters that are collected in offline mode.

Recognition of totally unconstrained hand-written characters is an attractive subject in the field of pattern recognition. Unlike English language, there has been only a few works on Arabic and Farsi characters recognition [10-14]. However, Farsi/Arabic texts have main specifications which make them difficult to recognize. Farsi/Arabic texts are cursive and are written from right to left. A Farsi/Arabic character might have several shape forms (1 to 4 shapes) depending on its relative position in the word. In addition, some Farsi/Arabic characters have the same shape and differ from each other only by existing of dots or zigzag bar. Figure 1 shows a sample set of upper case handwritten characters.

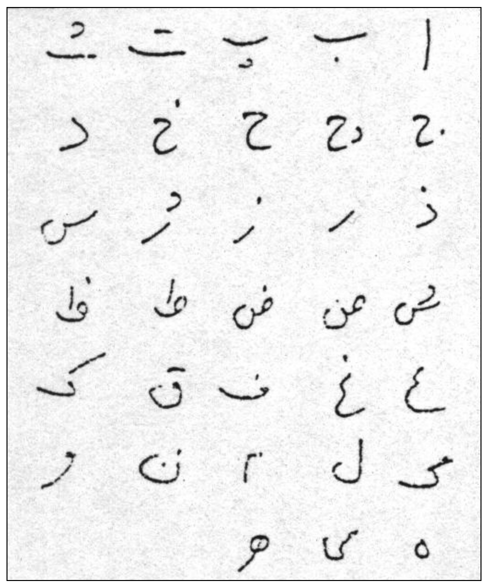

FIGURE 1: A sample set of Farsi Characters

The recognition algorithm, tolerates a high degree of style variation and distortion. Figure 2 shows this fact. However severely broken characters are mainly rejected by this algorithm.

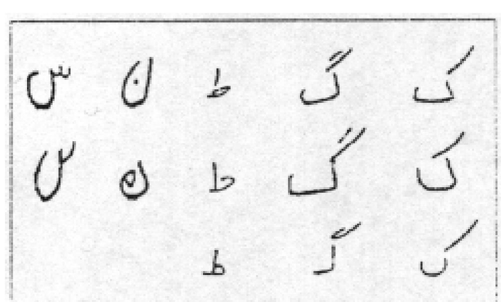

FIGURE 2: Style variation and distortion

Totally, almost all of the OCR systems have four stages [15], that each of them has its own problems and effects on the system. These four stages are Pre-processing; feature extracting [16-18], character categorization and Post-processing [19-22]. In this paper, we concentrate on these stages and present 2 methods for recognition of hand written Farsi characters. The remainder of this paper is organized as follows: sections 2 and 3 describe our proposed methods in details. Section 4 explains our dataset and illustrates experimental results for comparison our methods to each other. Finally section 5 concludes paper.

2. FIRST PROPOSED METHOD

In this method, first we describe pre-processing stage that consists of picture binary making and noise filtering in product scanning. There is property extraction of collected pictures next. In this part we give a picture body or a character to wavelet by border pixels as an input. The output is the properties that we want. The neural network is a simple and effective method of learning and training different samples that have efficient strength to noise. At the following subsections, we explain three stages pre-processing, feature extraction and recognition in this method in details. This method has no post-processing stage.

2.1 Pre Processing

In this step, binary making pictures and noise filtering are performed in scanning process. The saved pictures are in gray. Gray surfaces are necessary for defining the pen pressure and other information like that; but in suggested system only the main body of a structure is important and picture binary making causes the calculation volume decrease severely and program speed increases. Often the text optical character recognition systems are double characters pictures. In the proposed method the noises are cancelled first and then a picture is doubled. For noise canceling, total quantity of gray pixels is divided to the number of whole gray pixels and the resulting number is the grayness average of a picture. The threshold of grayness average is 10% of picture grayness and the pixels that are less than this limit are white pixels and the rest are black. While noise removing, we consider the dots as character's body.

2.2 Feature Extraction

In offline optical character recognition, the features are usually related to the items forms in pictures. The algorithm which is used for characters picture border pass is similar to the ones that described in [23] with small changes. The algorithm is designed for 8-neghbor connections and can detect the holes completely. After pass of letters picture border, the border following (cantor) is saved in $(x_1, y_1), (x_2, y_2), \ldots (x_N, y_N)$ that number N shows the picture border pixels. The border pixels are re-sampled in 128 pixels for normalizing N (number of border pixels) in the collected pictures, close coefficients finding and features extraction in detail as a whole.
Different methods are used for feature extraction from sample picture border like chain code and transform of border follow to Fourier transform that the transform parameters are used for feature extraction [24]. The wavelet transform is also like Fourier transform for feature extraction from item picture cantor. The method is in a way of giving the picture cantor to a switch or changer and we use it coefficient as a feature set for detection. This formation can be either in continuous (integral) or none continuous (total) that we considered centralized continuous wavelet in the current study. For each function of $l(t) \in L^2(R)$in wavelet transform with several degrees of separation we have Equation (1).

$$l(t) = \sum_{k=-\infty}^{+\infty} c_{j_0}(k)\phi_{j_0,k}(t) + \sum_{k=-\infty}^{+\infty}\sum_{j=j_0}^{+\infty} d_j(k)\psi_{j,k}(t) \qquad j_0 \in Z \tag{1}$$

In above equation, first addition of function with low resolution or coarse approximation is shown and the second addition shows approximation function with high resolution which increases with j of function detail raise and the quality rises. c_{j_0} Is the approximation coefficient in j_0 scale and the set of d_j are details of a signal in different resolutions. The wavelet transform used in the thesis is db1. For combining the coefficient in lower scale and gaining coefficient in higher scale, first the samples are taken up-sampling and then the resulting signal is filtered.

2.3 Character Recognition

As studied in previous subsection, our feature extraction method is wavelet transform. This method creates a feature vector for each character and then all of the vectors are normalized. In this method, our classifier is a neural network so at the next step, finalized vectors are taken to entrance layer of neural network as inputs. By consideration of the many examples and proper training, a neural network can recognize the samples that were not detected before which topic is useful for recognition of hand writings from a person to another. The applied neural network is Multi Layer Perceptron (MLP) that has 3 layers and each one is connected to the past layer. We train the network by an algorithm after mistakes derivation [25]. According to the point that we have 33 characters, the net output is made of 33 neurons that in system execution, the winner neuron shows the target character.

3. SECOND PROPOESED METHOD

In this method, first we divide input characters into five groups according to the number of their components and then use a set of appropriate moment features in each group and classify characters by the Bayesian rule. Finally, in a post-processing stage, some structural and statistical features are employed by a decision tree classifier to reduce the misrecognition rate. At the following subsections, we explain four stages pre-processing, feature extraction, recognition and post processing in this method in details.

3.1 Pre Processing

The input character is scanned at a resolution of 200 dpi and its binary image is smoothed. The smoothing process makes the primary grouping less sensitive to broken characters. Using a component labeling algorithm based on 8-connectivity [26], each character is segmented into its parts. If the number of black pixels in a component is less than a threshold value, that component is filtered out as a noise. This threshold value is adjusted to the pen thickness. Input characters according to the number of their parts and dots are assigned to one of the five groups, shown in Figure 3.

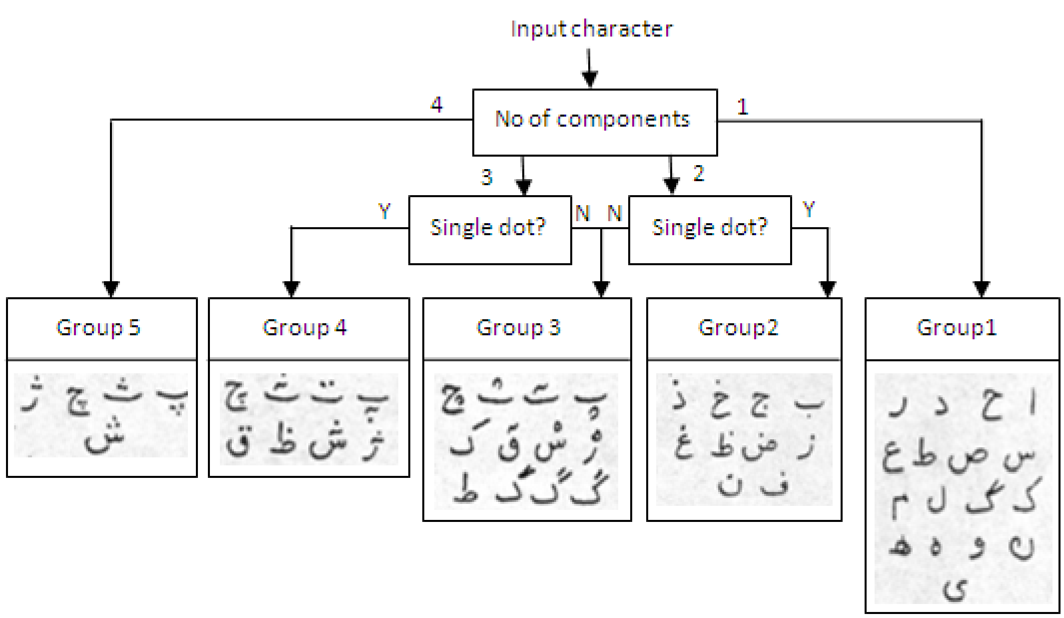

FIGURE 3: Primary grouping for input characters

3.2 Feature Extraction

In this method, the central normalized moments which are defined as Equation (2) and (3) are chosen as main features [26].

$$\mu_{pq} = \sum \sum_{(m,n)\in R} (m - \bar{m})^p (n - \bar{n})^q \; f(m,n) \tag{2}$$

$$m_{pq} = \frac{\mu_{pq}}{\mu_{00}^{\left(\frac{p+q+2}{2}\right)}} \tag{3}$$

If $f(m,n)$ is a binary image of character, R is a region where $f(m,n) \neq 0$, μ_{pq} is central moment and m_{pq} is normalized central moment. To select and appropriate set of moments, 25 moments for $p, q < 5$ were considered. Among these moments, m_{00}, m_{01}, m_{10} are always constant. From the remaining 22 moments, we select a set of moments for each group. Here an add-on feature selection method based on the total classification error was used [27].

3.3 Character Recognition

In this method, The Bayesian Rule was used for main classification. The distribution of features was considered to be multi dimensional normal one. The mean vectors and covariance matrices were estimated using the training samples for each class.

3.4 Post Processing

As shown in Table 1, some input characters are confused with other characters. For each output class we define a confusion set, consisting of the characters misrecognized in that class with an error rate more than 4%. For example the confusion set for the output classes “ح” and “ک” are “ع” and “ر ح ا گ و ن ل ک ع ط ص س” respectively. To improve the recognition rate, in a post-processing stage, for any output character having non-empty confusion set, a heuristically decision tree is used. Decision is taken on the basis of some structural features and also other classes put forward by the Bayesian classifier as the lower priority options. For example, if the output class is “ح” the character loci features of the upper parts of the characters is used to recover those “ع“ ‘s misrecognized as “ ح “.

Output class

Input character	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
0	41	0	0	0	1	0	0	0	5	2	0	1	0	0	0	0	0
1	2	38	0	0	0	0	0	5	3	1	0	1	0	0	0	0	0
2	0	0	47	0	0	0	2	0	0	0	0	0	0	0	0	1	0
3	0	0	1	40	0	0	0	0	7	1	0	0	0	0	0	0	1
4	0	0	0	0	26	18	0	0	2	0	0	0	0	0	0	0	4
5	0	0	0	0	1	42	0	0	5	2	0	0	0	0	0	0	0
6	0	0	2	0	0	0	44	0	1	0	3	0	0	0	0	0	0
7	0	7	0	0	0	0	0	40	2	0	0	0	0	0	1	0	0
8	0	0	0	0	0	0	0	0	32	16	0	0	0	0	0	0	2
9	0	0	0	0	1	0	0	0	5	42	0	0	1	0	0	0	1
10	0	0	0	0	0	0	0	0	2	0	46	0	0	0	0	0	2
11	0	0	0	0	0	0	0	0	0	0	0	50	0	0	0	0	0
12	0	0	0	1	1	0	0	0	2	0	1	0	29	0	0	1	15
13	0	0	0	2	0	0	1	0	1	3	0	0	0	42	0	0	1
14	0	0	1	0	0	0	1	0	0	0	0	0	0	0	32	11	5
15	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	48	0
16	0	1	1	0	9	1	0	0	0	0	0	0	2	0	1	0	35

TABLE 1: Confusion matrix for group 1 in a training stage (50 samples for training and 50 samples for test

Table 2 shows the effect of post-processing stage on the character in Table 1. As one can see, the total recognition rate is increased using post processing.

Input character \ Output class	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
0	46	0	0	0	1	0	0	1	1	0	0	1	0	0	0	0	0
1	2	45	0	0	0	0	0	0	1	1	0	1	0	0	0	0	0
2	0	0	47	0	0	0	2	0	0	0	0	0	0	0	0	1	0
3	0	0	1	48	0	0	0	0	1	0	0	0	0	0	0	0	0
4	0	0	0	0	46	1	0	0	0	2	0	0	0	0	0	0	1
5	0	0	0	0	5	42	0	0	2	1	0	0	0	0	0	0	0
6	0	0	0	0	0	0	49	0	1	0	0	0	0	0	0	0	0
7	1	1	0	0	0	0	0	46	1	0	0	0	0	0	1	0	0
8	0	0	0	0	0	0	0	0	47	1	0	0	0	0	0	0	2
9	0	0	0	0	0	0	0	0	0	47	0	0	0	0	0	0	3
10	0	0	0	0	0	0	0	0	2	0	46	0	2	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	0	50	0	0	0	0	0
12	0	0	0	1	0	0	0	0	2	0	1	0	40	0	0	1	5
13	0	0	1	2	0	0	1	0	0	3	0	0	0	42	0	0	1
14	0	0	0	0	0	0	2	0	0	0	0	0	1	0	45	2	0
15	0	0	0	0	0	0	1	0	0	0	0	0	0	0	3	46	0
16	0	1	1	0	1	1	0	0	0	0	0	0	1	0	1	0	46

TABLE 2: Confusion matrix for group 1 after post-processing

4. EXPERIMENTAL RESULTS

In this section we evaluate our proposed methods for recognition of hand written Farsi characters through two datasets. The first one consist of 6600 samples (200 samples for each character) written by different peoples and information of the other one is extracted from 420000 registration forms of national special talents high school and middle school tests [28].

For evaluation of the first method, wavelet function was considered Haar or db1. In property extraction for letters (33 categories), J_0 was 3. In other words, we sampled to level 3 from beginning level of sampling downwards. Therefore, approximation coefficient of wavelet function cA_3 was a vector with 17 entries and its details coefficients (cD_3, cD_2, cD_1) were 3 vectors with 66, 33 and 17 entries in orders from up to down. According to coefficients vectors measure, all the coefficients together will cause slowing the recognition process and more mistakes probably occur. Therefore, all the detail coefficient sets must be considered from the coarsest (level 3) to level 2. Then, we will have 67 specifications (17, 17 and 33) for every border pixels set. Specifications measures are normalized and saved in a vector of 134*1 for each picture.

The finalized vector is taken to entrance layer of neural network as an input which use reason is based on its actions. According to the point that we have 33 letters, the net output is made of 33 neurons that in system execution, the winner neuron shows the target letter. Therefore, the training and test sets are recognized with 95.17 % and 86.3 % accuracy.

We use confusion matrix for improving the results. Confusion matrix is usually used for training with an observer (and adaptation matrix without observer) [29]. The matrix finds similar classes to each other and decreases the categories numbers. In both cases of similarities, confusion matrix are gained that can be seen in Table 3.

Total Categories	Amount of similarity	Recognition of Train Samples (%)	Recognition of Test Samples (%)
33	0	95.17	86.3
26	Greater than 4 similarity	93.43	87.09
21	Equal and Greater than 4 similarity	97.24	91.51

TABLE 3: Letters Recognition with different categorizing numbers results

For the second method, Half of the samples were selected for the training and the other for the test. Table 4 shows the detailed results of the recognition process for each group in a training stage. As seen from this table, the post-processing stage improved the recognition rate for groups 1, 2 and 3 significantly.

Group	1	2	3	4	5
No Of Class	17	10	10	8	5
No of Moment	8	9	12	14	8
Recognition rate before Post-processing (%)	79.39	89.34	81.8	94	98.5
Recognition rate after Post-processing (%)	91.35	96.2	91.3	95	98.8

TABLE 4: No of features selected and recognition rate for each group in a training stage

Final result is shown as a confusion matrix in Table 5. The overall recognition rate in this experiment is 90.64%.

Output class

Input character	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33
1	94	0	0	0	0	0	0	2	0	0	0	2	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0
2	0	100	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	100	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	1	95	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0
5	0	0	0	1	98	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	99	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
7	0	0	0	2	2	0	76	0	0	0	0	0	0	8	0	4	0	0	0	0	0	0	0	0	0	8	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	90	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	1	2	0	5	0	0	0	0	0
9	0	0	0	0	0	0	0	1	98	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
10	0	0	0	0	0	0	0	0	0	88	0	1	0	0	0	0	0	0	5	0	0	0	0	0	0	1	0	0	3	1	1	0	0
11	0	0	0	0	0	0	0	0	0	0	96	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0
12	3	0	0	0	0	0	0	1	0	1	0	88	0	0	0	0	0	0	0	0	0	0	0	0	0	2	1	0	4	0	0	0	0
13	0	0	0	0	0	0	0	0	1	0	5	0	89	0	0	0	0	0	0	1	0	0	4	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	1	0	0	0	0	0	0	98	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	89	0	1	0	0	0	0	0	0	0	8	1	0	0	1	0	0	0	0
16	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	95	0	0	0	0	0	0	0	2	0	1	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	8	0	84	0	0	0	0	0	0	0	8	0	0	0	0	0	0	0	0
18	0	0	0	0	0	1	0	0	3	0	0	0	0	0	0	0	0	88	0	0	0	0	8	0	0	0	0	0	0	0	0	0	0
19	0	0	0	0	0	0	0	0	0	5	0	1	0	0	0	0	0	0	87	0	0	0	0	0	0	1	1	0	1	0	0	0	4
20	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	99	0	0	0	0	0	0	0	0	0	0	0	0	0
21	0	0	0	0	0	0	0	6	0	0	0	0	0	0	0	0	0	0	0	0	90	0	0	0	0	1	0	1	0	2	0	0	0
22	0	0	0	0	0	0	1	0	6	0	0	0	0	0	0	0	0	0	0	0	0	93	0	0	0	0	0	0	0	0	0	0	0
23	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	2	96	0	0	0	0	0	0	0	0	0	0
24	0	0	1	1	7	0	2	0	0	0	0	0	0	9	0	6	0	0	1	0	0	0	0	72	0	1	0	0	0	0	0	0	0
25	0	0	1	1	0	0	0	0	0	0	0	2	0	2	1	3	0	0	0	0	0	0	0	2	82	2	0	0	1	0	0	3	0
26	0	0	0	1	0	0	2	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	2	5	88	0	0	0	0	1	0	0
27	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	8	0	0	0	0	0	0	5	86	0	0	0	0	0	0
28	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	2	95	0	0	0	0	0
29	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	8	0	0	1	0	0	90	0	0	0	1
30	0	0	0	0	0	0	0	0	0	2	0	2	0	0	0	0	0	0	2	0	0	0	0	0	0	2	0	0	1	90	1	0	
31	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	6	0	0	0	0	0	0	0		1	0	7	0	82	2	2
32	0	0	0	0	0	0	0	0	0	0	0	0	0	0	6	0	0	0	0	0	0	0	0	0	0	2	0	0	6	0	2	83	1
33	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	2	0	0	0	0	0	2	1	93

TABLE 5: Confusion matrix for second proposed method in recognition algorithm

5. CONCLUSION

In the current study we proposed a system for automatic recognition of hand written Farsi characters. For this purpose; we proposed two different methods based on neural networks and a special post processing approach to improve recognition rate of Farsi uppercase letters. In the first method, we extracted wavelet features from borders of character images and learned a neural network based these patterns. In the second method, we divided input characters into five groups according to the number of their components and used a set of appropriate moment features in each group and classified characters by the Bayesian rule. In a post-processing stage, some structural and statistical features were employed by a decision tree classifier to reduce the misrecognition rate. Our experimental results are shown suitable recognition rate for both methods.

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