

A Novel Method for Recognition of Persian Alphabet by Using Fuzzy Neural Network

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ABSTRACT This paper presents a system that can recognize handwritten words expressed using broken letters of the Persian alphabet. The proposed system can be used for most activities related to the gathering of public information. Statistical features of the separated/broken letters are employed in the system. Each letter is recognized using interconnected fuzzy neural network. The advantages of this method include high precision owing to the strength of the neural network algorithm and the possibility of extending dataset instance codes in a simple manner. At last, an evaluation for the proposed method is provided experimentally.

INDEX TERMS Persian alphabet recognition, letter partitioning, smoothing, method for searching context line.

I. INTRODUCTION

The human brain consists of a series of interconnected neurons that facilitate various human activities such as reading, breathing, moving, and thinking. In the case of learning, the human brain is more powerful than microprocessors. Based on this fact, researchers working on the “backward propagation grid” are attempting to adapt the capability of the human brain to learn from experience [1]. Backward propagation is probably the most common method for training neural networks without the use of forward propagation. In forward propagation, given an input pattern, the real output is propagated using networks and suitable methods. Backward propagation employs suitable exits based on the input patterns, and it updates the extents based on the error signal. Although hundreds of studies on backward propagation can be found in the literature, the methods proposed in most such studies employ large numbers of equations and complex partial differential equations with indefinite variables to transmit a simple concept. A quasi-instruction algorithm (quasi-program) or an example accompanied by a picture are often the most impressive methods to transmit information. Backward propagation continues to be the best method for optical character recognition. However, the long time needed to arrive at the best character recognition result is a major drawback of this method [2], [3].

Even so, the pre-processing phase of character recognition in the propagation process is less complex than that in a genetic algorithm [4].

Genetic algorithm is applied to optimize the deficiencies of the standard backward propagation network, which refer to architectural structure and initiative extents. These algorithms are often used to find a neural solution for complex problems by achieving compliance between the natural choice rule and a genetic science concept called “ANSAB conservation.” To increase accuracy and authenticity and to reduce teaching time, genetic algorithm concentrates on the best architectural possibilities and the best initial quantities of measure for use in the backward propagation structure. By applying genetic algorithm, the measures of a neural network can be optimized outside via effective and fast learning. Genetic algorithm complies techniques of research and optimization which follow natural evaluation principles. Genetic algorithm has been proposed as potential candidates for optimizing the extent parameters of neural networks.

A backward propagation network contracted to execute descending learning algorithms is faced with vicissitudes when it encounters minor local problems [5], [6]. While genetic algorithm is not comprising at least one general way, it can present a relatively optimized solution significantly

faster than conventional and normal methods and yield good results.

In this paper, a novel method is proposed for learning through backward propagation in a neural network to recognize optical characters. A genetic algorithm is applied to determine which architectural structure should be applied to define the initial extents of the network.

II. RELATED WORKS

A. LITERATURE REVIEW

Based on the importance and the wide range of applications, as well as the intense needs of global commerce, research on optical grapheme readers has grown in universities, government organizations, and private companies [7]. Unfortunately, distinct statistical information on this body of research is not available. Even so, it is well known that an efficient commercial optical grapheme reader for printed texts has not been developed thus far, and we hope that one would be developed as a result of our country's efforts in this field. A few attempts in this field are noted in the following section:

Most studies in the literature pertaining to optical grapheme readers have focused on methods for internal-partitioning, redisplaying, and recognition of letters. Whereas other aspects, such as pre-processing, external-partitioning, and post processing, have been studied relatively rarely [8], [9].

Based on these facts, a national plan to recognize printed texts and a limited volume of handwritten texts was initiated and executed by Dr. Ehsanollah Kabir. As a result, many students and professors from University of Amirkabir and University of Tarbiatmodarres wrote their papers on this subject. In addition, Dr. Kabir has researched the "Recognition of Persian printed texts" from the viewpoint of organizing the scientific and industrial studies on "Recognition of Persian handwritten letters and numbers" in Iran.

Practicable attempts on a wide commercial scale were initiated to cater to enrollment into the program "Training brilliant talents" in the year 2001. Enrollment was done by means of application forms that were filled by students. Similar to national examinations, students participating in the exam were required to write down their name, surname, father's name, province of birth and current accommodation address, school name, and religion in square boxes in an interrupted manner (each word was to be written in one square box). All forms were sent to the central examination-conducting organization, and many typists performed the task of reentering the data from the forms into a computer. The typists typed the letters in the forms to digitize the students' identification certificates. This method was time consuming, and many typists were required. Moreover, it was possible that a typist could enter a name falsely, in which case a non-existent person would be created in the system. Moreover, this way of doing things is proved to be expensive. To solve this problem, in the year 2001, Andishe Narmafzar Paya Company started

work on an optical grapheme reader system to recognize interrupted handwritten Persian letters. The product developed by this company can combine individual handwritten Persian letters after recognition. The words created in this way are searched against a dictionary (that contains names and surnames), and the recognition errors could be reduced dramatically. Because the letters were written interruptedly and the students wrote their names accurately and clearly (because they wanted their identification certificates to be readable), as well as owing to the use of a dictionary. The recognition accuracy achieved by this product was satisfactory (correct recognition rate of up to 90%) [3].

In the years 2002 and 2003, 440,000 "brilliant" students were enrolled using this product. In the first year of application of this product in 2002 (First sample), the cost and the time required for enrollment decreased by 45% and 25% respectively. In the next year, both numbers decreased by 50%. The recognition accuracy of the software applications employed for enrollment in these examinations differed in each part, but overall it had a perfect performance.

B. PROBLEM DEFINITION

The Persian alphabet consists of 32 letters, and the appearances of these letters change depending on their position in a word. The complete features of these letters are mentioned in [3], and we mostly consider this subject from the application viewpoint. "Point" is one of the most important and integral parts of Persian calligraphy. A few words can be distinguished based only on their points, and such words would be indistinguishable from each other without these points [10], [11].

Owing to considerable similarities among Persian letters such as (س،ش،ص،ض،ط،ظ)، their separation is problematic, and a fuzzy neural network capable of separating these letters should necessarily include a large number of local features [8]–[10]. At first, appropriate groups of letters are defined using classification algorithms, trial and error, and witnesses. Then, a neural network called "MLP" is employed to separate these groups from each other [12], [13]. The initial proposed classification is achieved using witnessed criteria. For instance, we have "ب،پ،ت،ث" in one group. Then, "MLP" is employed to distinguish these groups from each other, and it indicates that this group is defined well but practically there are some groups that cause mistake. In this case these two groups construct one bigger group (for instance "س،ش" and "ص،ض") also by application of vector quantization and training algorithm "LBG". "LBG" by using Euclidean interval criterion is tried to limit the number of each group's members and smaller groups containing fewer members would be created. Classification and training must be repeated to the extent that the network can distinguish groups with the maximum number of them [14]. The selection criteria is appropriate classification of the final MSE after training and reaching to this MSE and "end of training" criterion, relative end of changes of MSE is selected [15].

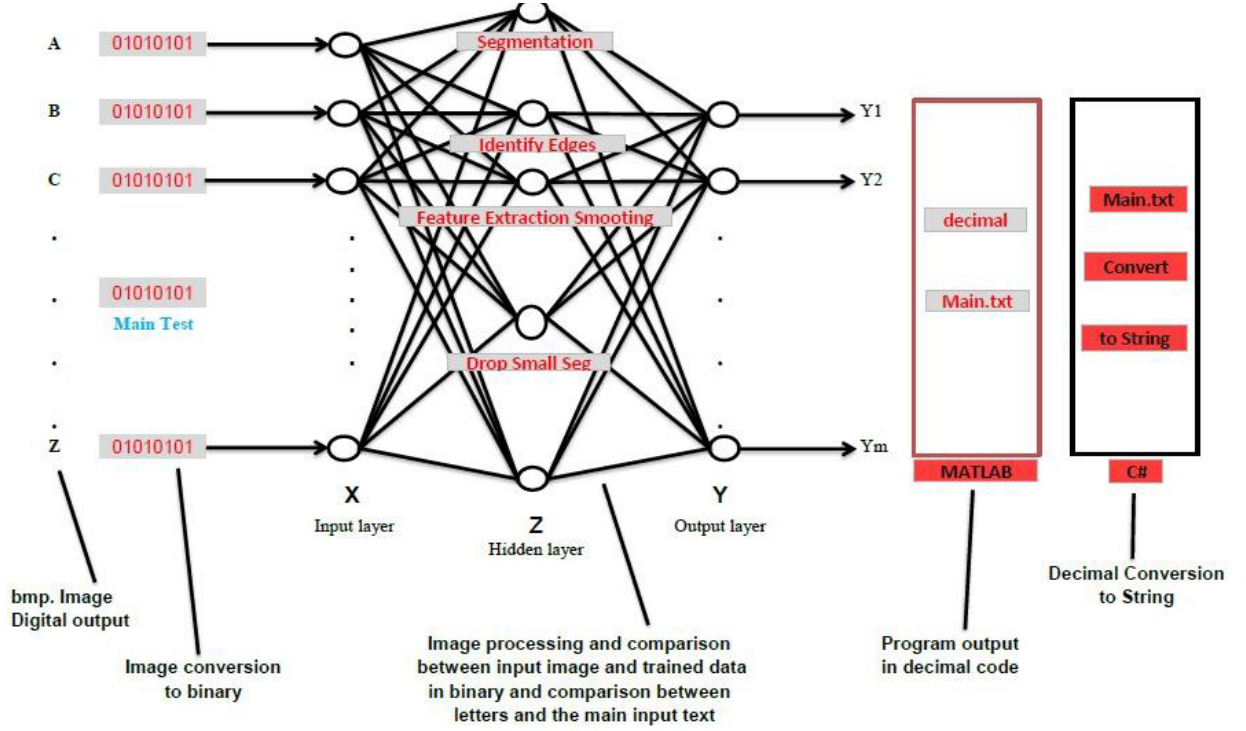


FIGURE 1. Schematic diagram of proposed method for Persian letter recognition.

III. PROPOSED METHOD

A schematic diagram of the proposed method is shown in Figure 1.

A. ALGORITHM

The algorithm of the proposed method is following:

- 1 - Loading a file for image processing.
- 2 - Database creation based on existing training data and fresh input to neural network.
- 3 - Conversion of graphic data to binary data (for training data and fresh input).
- 4 - Comparison of training data with new image defined as input to network.
- 5 - Consideration of error and noise reduction.
- 6 - Output of compared data in the form of decimal codes and subsequent storage of the output.

B. ALGORITHM CODING AND FUNCTIONS

1) ALGORITHM CODING

The coding and description of the algorithm is shown in Table 1. In this algorithm, an educational example should be input and calculate the network output.

2) BAK FUNCTION

The Bak function is the main function used to train the neural network. Within this function, another function called Alpha4train is defined and used to train data for neural network. Later, the Bak function of the trained data are stored in a file called "mynet.mat" which is shown in Figure 2.

TABLE 1. Algorithm coding and symbols.

Algorithm coding
Enter educational example and calculate network output
Calculate $\delta = o_k(1-o_k)(t_k-1)$ Use Saig mode function $F(x) = 1/e^{-x}$
Calculate nodes of hidden parts $\delta_h = o_h(1-o_h)\sum_{k \in outputs} w_{hk}\delta_k$
Update network extents $w_{ij} = w_{ij} + \Delta w_{ij}$
Points
W_{ij} : input extent of hidden layer
W_{hk} : input extent of external layer
O_h : real output for nodes of hidden layer
O_k : real output for nodes in exit layer
T_k : desirable output
δ_k : signal errors in node exit layer
δ_h : signal errors in hidden layer nodes
η : learning rate

3) DATA INPUT IN FIRST STEP

In this study, considering the appearance of each letter in the Persian alphabet, 100 training data was employed as the input to the neural network.

Variables in C:\Users\hamed\Desktop\OLD FILE\old desk\Ocr_final\data base\mynet.mat				
Import	Name	Size	Bytes	Class
<input checked="" type="checkbox"/>	Alphabet	315x5400	13608000	double
<input checked="" type="checkbox"/>	H1	1x1	8	double
<input checked="" type="checkbox"/>	Q	1x1	8	double
<input checked="" type="checkbox"/>	Qa	1x1	8	double
<input checked="" type="checkbox"/>	S1	1x1	8	double
<input checked="" type="checkbox"/>	S2	1x1	8	double
<input checked="" type="checkbox"/>	Target	6x5400	259200	double
<input checked="" type="checkbox"/>	errr	6x5400	259200	double
<input checked="" type="checkbox"/>	net	1x1	7779491	net
<input checked="" type="checkbox"/>	tr	1x1	74300	structure

FIGURE 2. Stored trained file named mynet.mat.

```

be1 =imread('be1.bmp');
be2=imread('be2.bmp');
be3 =imread('be3.bmp');
be4 =imread('be4.bmp');
be5 =imread('be5.bmp');
be6 =imread('be6.bmp');
.
.
be96 =imread('be96.bmp');
be97 =imread('be97.bmp');
be98 =imread('be98.bmp');
be99 =imread('be99.bmp');
be100 =imread('be100.bmp');

```

FIGURE 3. Input of images to neural network by using imread function.

For example, “٠.bmp” files are used as input data for the “imread” function as is shown in Figure 3.

In the Alpha4train function, data are read as input and are stored in the form of a matrix as shown in Figure 4.

<code>function [Alphas] = Alpha4Train(rw,cl)</code>
<code>.</code>
<code>ba4T=ba4Train(rw,cl);</code>
<code>be4T=be4Train(rw,cl);</code>
<code>Pe4T=pe4Train(rw,cl);</code>
<code>P4T=P4Train(rw,cl);</code>
<code>.</code>
<code>Te4T=Te4Train(rw,cl);</code>
<code>Tee4T=tee4Train(rw,cl)</code>
<code>.</code>

FIGURE 4. Conversion of input images and subsequent storage in matrix form.

After training the neural network and generating “mynet”, the proposed algorithm uses “mynet” in conjunction with the “ImProc” function to execute the image processing tasks.

This function summons the text that is to be subjected to image processing operations as the input, as is shown in Figure 5.

4) WORKING WITH “ImProc.m” FUNCTION

This function provides an image with Persian text as input to the software application. Then, this image is converted into the matrix form.

The “ImProc” loop function considers the image line-by-line and subjects it to the image processing operation. This operation is performed by using the functions “IdentifyEdges”, “Segmentation” and “DropSmallSeg”, as is shown in Figure 6.

At first, the input is considered line-by-line, then the words and sentences are selected. Finally, the selected letters are accumulated in a variable.

5) FEATURE EXTRACTION SMOOTHING FUNCTION

This function distinguishes the letters of the selected objects (words and sentences), and it employs image improvement methods to ensure that the letters are readable and recognizable. The letters are separated and compared against the initial database by using the “Recognition function”.

These converted data are stored in the form of decimal codes in a text file. The processing and conversion operation is now completed.

A number is converted to a string by using codes written in C# programming, as is shown in Figure 7.

Figure 8 is the program for converting decimal outputs of the neural network (decimal) into a string. The steps followed in the present study can be summarized briefly as follows:

A diverse database containing forms with different handwritings, including interrupted handwritten letters, was provided at first. Appropriate information about the required dictionary was collected, and the first names of the male and female students appearing for an examination were documented in the dictionary. Then, the information collected

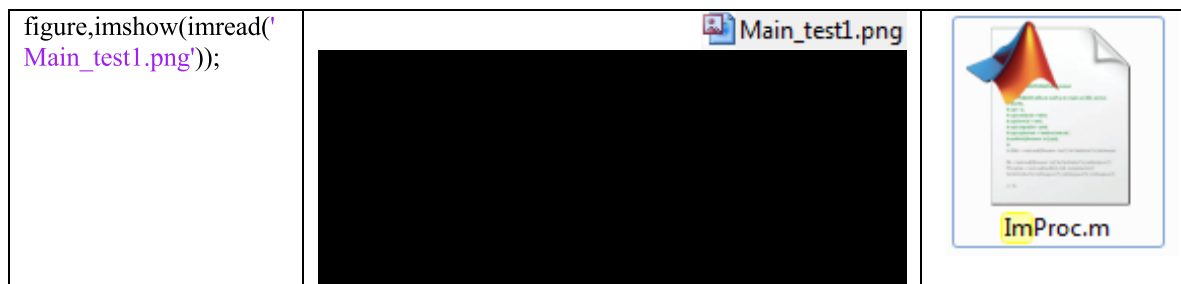


FIGURE 5. "ImProc" function for image processing tasks.

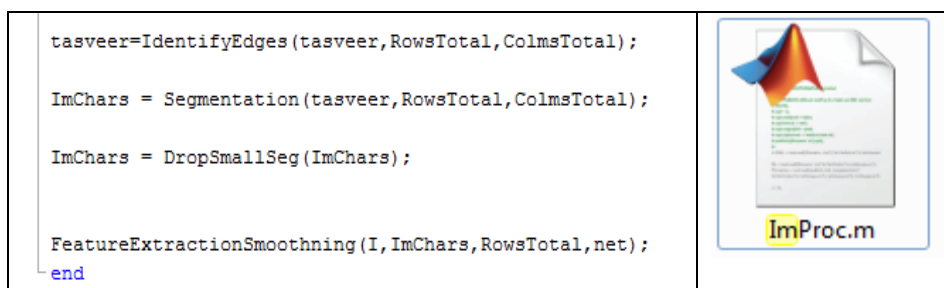


FIGURE 6. ImProc function.

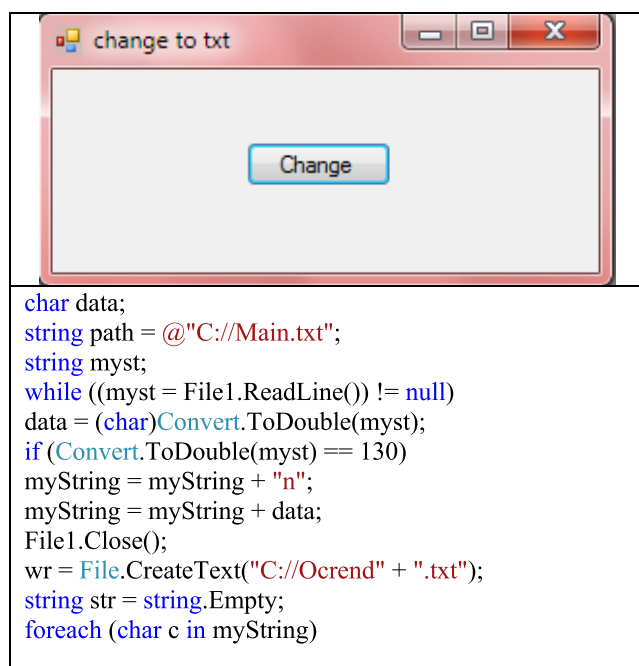


FIGURE 7. Conversion function with C# codes.

about words was used to test and examine a connected neural network, and a statistical linguistic analysis algorithm was developed to correct the errors in the recognition system based on the aforementioned dictionary. To correct possible errors in the collected handwritten letters and the dictionary, the associated data were filtered manually.

An example of the input words is shown in Figure 8.

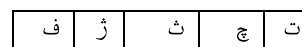


FIGURE 8. Sample of filled form.

The input images were pre-processed at first, which involved reading the image file of each character, eliminating noise, and dividing each letter into two categories. In the next stage, exact features were extracted from black-and-white images, and the extracted features were sent to the decision-making stage, which was composed mainly of interconnected neural networks.

The output of this stage, the number of characters recognized from the alphabet table was processed using the aforementioned statistical linguistic analysis algorithm to eliminate possible errors. In this stage, the database of recognized characters was compared against the existing dictionary, and the final results were obtained.

IV. EVALUATION OF PROPOSED METHOD

In this section, the proposed method is evaluated. The results obtained by applying the method to four texts are presented. The performance of proposed method is shown in Figure 9 and Figure 10.

Figures 9 and 10 show bar and line charts respectively of the simulation results obtained using the proposed method. As shown in these charts, the accuracy of the proposed method in terms of the recognition of Persian manuscripts is high, and the noise is very low. Moreover, the increase in execution time relative to the increase in accuracy is within reasonable limits. The results obtained for each of the four

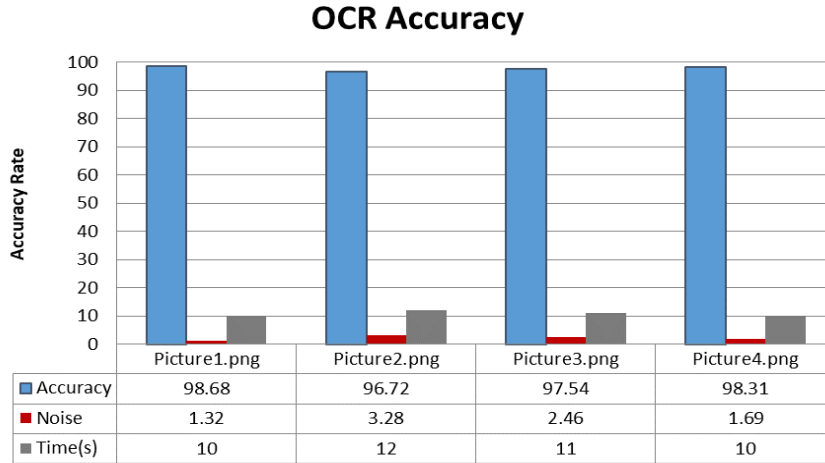


FIGURE 9. OCR Performance of proposed method in bar chart form.

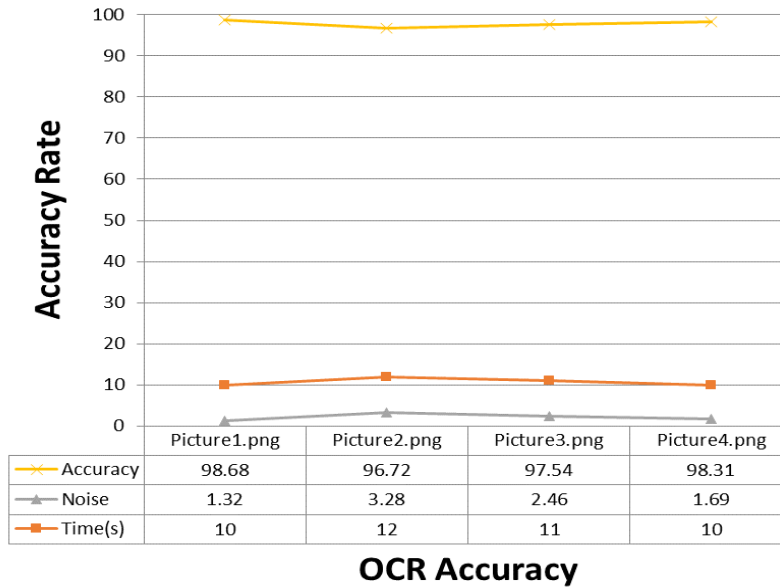


FIGURE 10. OCR performance of proposed method in line chart form.

texts are approximately identical with very minor differences in the case of each of the three parameters. These results indicate the proposed algorithm is very effective and can be used for Persian handwriting text recognition with high accuracy and low noise and within reasonable time.

The advantages of the proposed method are as follows:

(1) High accuracy owing to the strength of the neural network algorithm. The proposed algorithm can be implemented on computer systems to recognize Persian language words and sentences in different manuscripts with a high rate of successful estimation.

(2) The proposed algorithm makes it possible to extend dataset instance codes without incurring the high costs associated with changing details because it is based on various forms of the alphabet independently.

V. CONCLUSION

In this paper, we proposed a method that can recognize handwritten Persian letters and words. The proposed method was trained using educational samples. Then its functionality was evaluated using experimental samples. The experimental results obtained at different stages of the recognition system were presented in Section 4. In the future, we plan to improve the word recognition performance of the proposed method by incorporating vocabulary knowledge in the search algorithm.

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