A Method based on Decision Trees and Neural Network for Recognition of Farsi Handwritten Digits

Navid Samimi Behbahan*
Department of Computer Engineering, Omidiyeh Branch, Islamic Azad University, Omidiyeh, Iran Phone: +98 938 8949749

Abstract: *Farsi handwrite character recognition is a main topic in pattern recognition, machine learning, image processing, machine vision and data mining. Handwrite character recognition has many applications such as licenses plate recognition, document annotation by keywords, postal code recognition, bank check processing, entry score system in university. In handwrite recognition confront with some difficult such as different type, written with different pressure, using a thick or thin pen. In general there are three major stages in the character handwrite recognition problem: (1) preprocessing that proceed to normalization, noise removing and segmentation, (2) Feature extraction tries to replace the image with numerical feature vector in order to describe image as well. (3) Classification phase try to recognition of handwrite character with high accuracy by using extracted feature. In this research, we using of Structural features and some of character numeral feature to recognition handwrite digit. Percent of recognition of this method for handwrite digits achieved 98.18% .*

Key words: Persian handwritten numbers, features extraction, decision tree, neural network

1. Introduction

Recognizing handwritten numbers is one of the significant problems within the area of light letters cognition, which is of much application. As an example for handwritten numbers recognition systems applications, reference could be made to reading digital data put into forms. The use of a practical handwritten numbers recognition system faces a number of challenges of which the most important would be the necessity for a high level of recognition rate. In the field of Persian language, simply because of great similarity among digits in addition to differences in the way they are written, creating a recognition system with an acceptable degree of exactitude for practical purposes comes across some difficulties. It is for this reason that expanding methods to improve their precision would be of necessity. During the last few years, various works have been done over the issue of Persian and Arabic handwritten numbers and letters' recognition. In a piece of research conducted by Darvish et al, a shape congruence algorithm is made use of to recognize Persian handwritten digits. For each and every sampling point on the shape's connector, description is arrived at by means of the placement distribution of other points' connector(s) [1]. In another piece of research by Parvin et al, another method for improving upon the functionality of recognition system has been put forward. The original idea in the suggested method would be use of classifiers on a binary basis [2]. In yet another research by Alizadeh et al, some methodology based on genetic algorithm to make a neural network grouping using a classifying pick-up method of giving weights based on opinion has been propounded [3]. The research conducted by Shahabi and Rahmati, use has been made of Gabor filter banks which is suitable for the construction of Persian handwritten texts in addition to visual system [4]. Still in another work by Parvin et al, application has been made of categorizing even classifiers to boost this group of classifiers. These can reduce the error rate for more precision in features space [5]. Another research has used Bays' classification moment torque to recognize Persian handwritten digits [6]. Masroori has applied dynamic temporal torsion algorithm to recognize the numbers [7].

What we have done is based on bringing out a series of constructional features from amongst the set of handwritten numbers. These features are the existence of an enclosed space within the digit, branching-out and terminal points, the directionality of semi-circles and the degree of pixel density in various areas. Later on, the genealogical decision-making tree would have been created upon such features to be evaluated.

Mention would be made of what has been said in various sections as this article goes on. In the second part, the focus of attention has been on introducing the dataset applied. In the third part, the preprocessing stage is brought to attention which includes how to drop noise and extract digit skeleton. In the fourth part, we shall talk of the methodology of bringing out features. The fifth part is devoted to classification stage. In the end, will come the results out of the suggested model.

2. Hoda dataset features

Hoda database which is documented upon by researchers is also of good use in this research. The Hoda handwritten numbers set is the first sizable Persian handwritten numbers comprising of 102353 samples of black and white handwritten digits. This set has been made during a Master's degree project concerning the recognition of handwritten forms [8]. The data within this set have been extracted from something around 12000 registration forms of M.Sc. entrance examinations of 2005 in addition to the Associate's examinations in Applied and Science Comprehensive University in the year 2004. The properties in this dataset are as follows:

The sample separablility degree: 200 points per inch
The total number of samples: 102352
Educational samples numbers: 6000 samples of each class
Experimental samples number: 2000 samples in each class
Other samples: 22352

3. Pre-processing Step

Preprocessing consists of two stages of making figures size identical and framing each digit to be transformed into much less pixels. Identicalization is done through converting all figures to 90 rows and 70 columns of pixels. In addition, each frame size has been considered to be 10×10. The considered frame is moved on the image. If there are more than 40 bright pixels in each area, the pixel quantity is black; otherwise, white pixel is reflected back. So that (based on figure 3), a 90×70 image is converted to 9×7.

Figure 2: Preprocessing & normalization of handwritten digit of three

4. Feature Extraction

We put together dents of each figure in four possible directions (left, right, up and down) and attain a dataset with 32 features for each digit (Figure 3). You can see the feature vector of number 3 in table 4.

Figure 3: Image view of number 3 from four directions

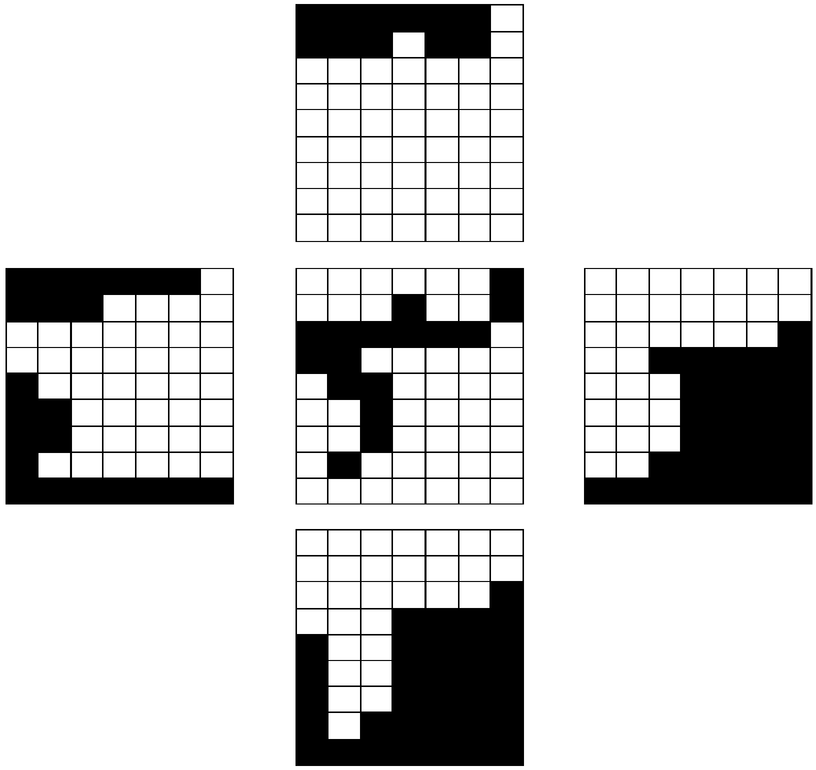
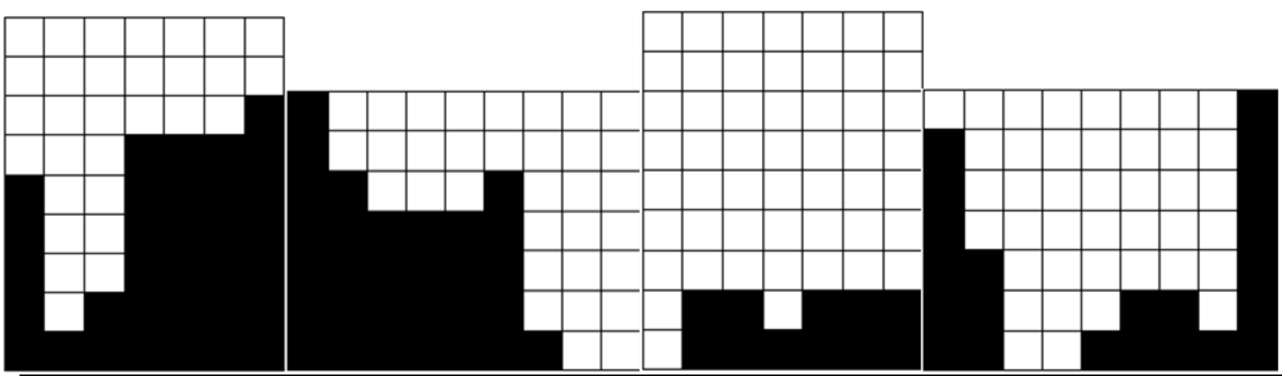


Figure 4: Extracting feature vector from the image of digit '3'

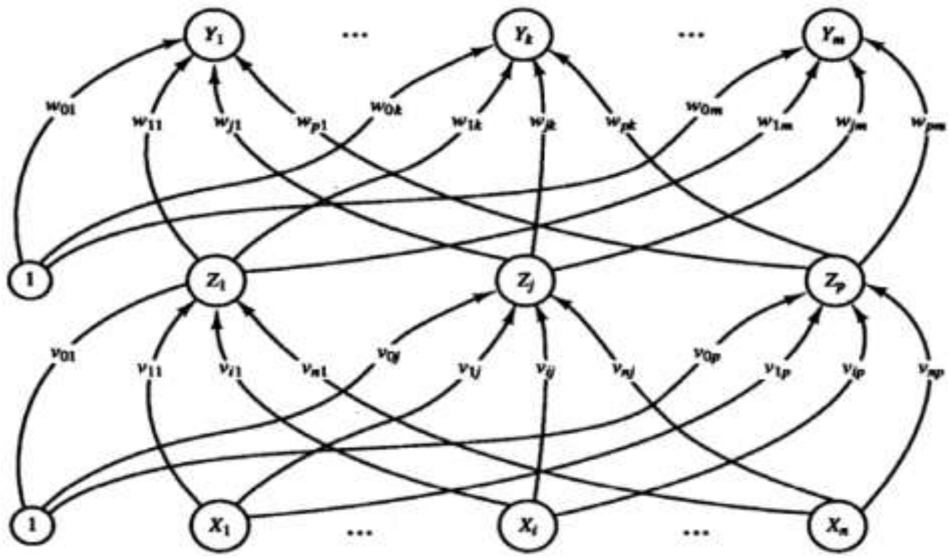


5	1	2	6	6	6	7	7	5	4	4	4	5	1	0	0	0	2	2	1	2	2	2	6	3	0	0	1	2	2	1	1

5. Back-Propagation Neural Networks

There are so many methods for training network and out banding the weights so as to reach a significant error. One of the most famous of these methods is error back propagation algorithm. This algorithm which was proposed by Rommel Hart & Mac Kelly Land in 1986, are applied in feed forward neural network. Feed forward means that artificial neural neurons have been placed in successive layers and send their output (signal) forward. Morover, the word "back-propagation" spells that the error is fed back into the network to outbalance the weights and to, then, reiterate the entrance to its in-route down to the exit. The back-propagation procedure on errors is one of supervisory methods which mean that: the in-specimen has been tagged and the out- ones expected of each of them are already known. As a result, the network's output has been compared against these idealized exits simply in order to calculate the error on the network. The network's weights are supposed to have been opted randomly in this algorithm from the word go. The network's output is calculated in each step to be corrected according to its discrepancy with the idealized output so much so that the said error comes down to its minimal at the end [9].

Figure 5: The backward propagation network architecture (the entrance layer being X, the hidden layer being Z, and the exit layer nominated Y. w and v are weights inside the network)



As to the continuation of this work, algoritsms relating to the backpropagation neural network (figure 6) and the recognition of the pattern under evaluation in this type of network (figure 7) have been presented [10].

Figure 6: Back-propagation network educational algorithm

Step 0. Set σ, α
Initialize Weights W and V with small random values
n: Input
p: Hidden units
m: Output units
Step1. While MSE done reach to a small value or for many times do step 2 – 10
Step2. Set X as input neurons
Step3. Find Zin , Z
For (j=1..p)
$Zin_j = \sum_{i=0}^{n} X_i V_{ij}$
$Z_j = f(Zin_j)$
$Z_0 = 1$
Step4. Find yin, y
For(k = 1 .. m)
$Yin_k = \sum_{j=0}^{p} Z_j\ W_j\ k$
$Y_k = f(Yin_k)$
Step5. Find δK_k
$K = 1 .. m$
$\delta K_k = -[t_k - y_k].\sigma.y_k(1-y_k)$
Step5. Find δj_j
$j = 1 .. p$
$\delta K_k = (-\sum_{k=1}^{m}(\delta K_k W_{jk}) . \sigma . Z_j . (1 - Z_j))$
Step7. Find ΔV_{ij} **by:**
$i = 0..n,\ j = 1..p$
$\Delta V_{ij} = \alpha.\ \delta J_j.X_i$
Step8. Find ΔW_{jk} **by:**
$j = 1..p,\ k = 1..m$
$\Delta W_{jk} = \alpha.\delta K_k.Z_j$
Step9. Find V_{ij} **by:**
$i = 0..n,\ j = 1..p$
$V_{ij} = V_{ij} + \Delta V_{ij}$
Step10. Find W_{ij} **by:**
$j = 1..p,\ k = 1..m$
$w_{jk} = w_{jk} + \Delta w_{jk}$

Figure 7: algorithm to test a sample (in the very stage of be in tested) inside the neural network

Step0. Set σ, α
Initialize Weights W and V with small random values
n: Input
p: Hidden units
m: Output units
Step1. Set X as Unknown Pattern
Step2. Find Zin, Z
For (j = 1..p)
$\mathbf{Zin_j} = \sum_{i=0}^{n} X_i V_{ij}$
$\mathbf{Z_j = f(Zin_j)}$
$\mathbf{Z_0 = 1}$
Step3. Find yin, y
For (k = 1..m)
$\mathbf{Yin_k} = \sum_{j=0}^{p} Z_j W_j k$
$\mathbf{Y_k = f(Yin_k)}$

6. Actualization Results

4500 samples of the data set of Hoda were extracted prior to the start of the simulation, the entrance data having been classified into two groups by us.

1. Educational Data: these were employed from among the label data. Of the total number of 3000 of specimen data (i.e., around 67%) were selected at random, having been put to use as educational data. Upon the network having been educated by these data, the weights found their final measure so that the network came down to the lowest possible minimal of 3.2237 errors.

Table 1: Results of performance and amount of correct examined samples of each class

digit	Number of correct examined samples	Number of incorrect examined samples	percentage of correct examination
0	141	9	94%
1	135	15	90%
2	126	24	84%
3	121	29	81%
4	142	8	95%
5	144	6	96%
6	137	13	91%
7	141	9	94%
8	149	10	93%
9	146	4	97%
sum	1357	143	91.53%

Table 2: Value of used parameters

variable	Initial value
σ	2
α	0.5
n	32
p	24
m	10
Number of execute algorithm	100000 times
Wight amount (v,w)	Random amount between 0 and 1
layers Number	3
Used sigmoid function	$f(x) = 1/(1 + e^{-x})$

7. Conclusion

It was on the Hoda data set that the suggestive algoritms set were downloaded, put into practice, and assayed. The number of neurons in the hidden layer was spotted (24 neurons) trough the method of trial-and-error. The average bundling came out to be 100% for the educational data, and about 89.18% for experimental data.

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