A Probabilistic Neural Network to Recognize Handwritten Digits using Boundary Descriptor Properties

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Abstract - Recognition of handwritten digits is a challenging task, because the writers may possibly write with dissimilar styles, sizes, width and shapes. A probabilistic neural network for recognizing handwritten digits is proposed here. Normalization of the digits of varying sizes is done for getting better boundary descriptor properties. The different boundary descriptor features extracted for recognition are compactness, eccentricity, equivalent diameter, extent and solidity. Classification of these features is done with probabilistic neural network. These features are tested on MNIST digit data set and observed good results.

Index Terms: Hand writing recognition, Boundary descriptors, Feature extraction, and Probabilistic Neural Network, Optical Character Recognition.

I. INTRODUCTION

Handwritten numerical character recognition has been an intensive research in the field of artificial intelligence for last few decades. Offline handwritten recognition represents an extensively more difficult problem than on-line recognition or typed optical character recognition (OCR). Off-line recognition is performed on a scanned image of handwriting and thus contains no chronological data. The unconstrained character of this approach more complicates the problem. Past handwriting algorithms have typically had a limited lexicon or bank check reading in addition to identified regions of text [1, 2].

The implementation described in this paper assumes a traditional approach to recognition: pre-processing, feature extraction from the boundary of image, and classification with neural networks. Pre-processing on the input data converts it to a binary image, removes noise, and does size normalization. The feature extraction will present the classifier with boundary descriptors data. Features calculated typically include compactness, eccentricity, equivalent diameter, extent and solidity. Thus it is significantly important that characters be as similar as possible transversely written with varied writing styles and sizes.

The classification is performed using probabilistic neural networks. The neural networks are commonly used for image recognition [3, 7, 11]. In this neural network, the data is classified using the radial basis training method. As a rule of such classifiers, have a combination of layers of neurons and all the neurons have differentiable characteristics [7, 11]. During the training process the synaptic weights of the connections among all neurons are modified. The classifier is tested on MNIST handwritten numerical data. The MNIST database contains 60,000 samples of handwritten digits in training set and 10,000 samples of handwritten digits in the test set. A variety of methods are available to answer this problem [4, 5, 6, 8, 9, 10]. For estimation of the method efficiency, the most significant parameter is error rate. This parameter shows which samples in the database are recognized inaccurately. Different classifiers proved on this handwritten characters [13, 14, 15, 16] has publicized error rate varying between 2.25 to 10.0%.

Figure 1 shows the stages of the recognition process. Section 2 describes the pre-processing approach for transforming the input image into a normalized image and now the normalized image is transformed to boundary image. In section 3 the boundary descriptor feature extraction method is described. The classification process and its results are presented in Section 4. The conclusion is given in the final section.

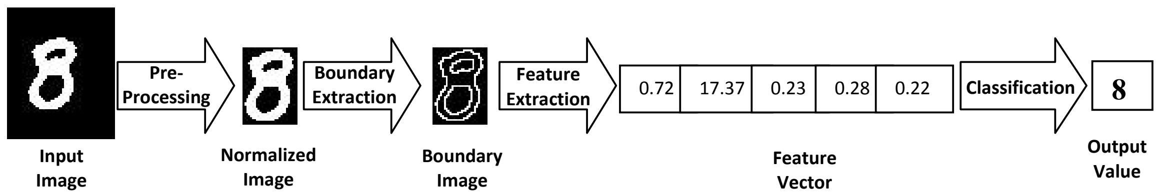

Figure 1. Overall process of the recognition system

II. PRE-PROCESSING

Pre-processing is required for the digit images, because all the samples are not having same size, width or style. First, all the input images are normalized to a 64 X 64 pixel size. These images are converted to binary by calculating the threshold of the image. From the binary images boundary images are extracted to extract the features. The boundary of a set *A*, denoted as β (*A*), can be obtained by first eroding *A* by *B* and then performing the set difference between *A* and its erosion as follows: $\beta(A) = A - (A \ominus B)$. This process is indicated in Figure 2.

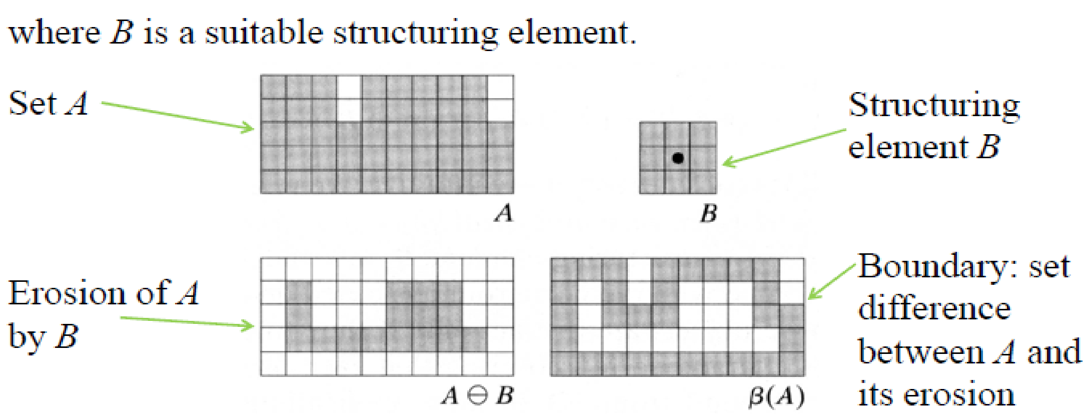

Figure 2. Boundary of the set A

III. BOUNDARY DESCRIPTOR FEATURE EXTRACTION

Geometrical shapes possess certain features that hold adequate information for recognition of the objects. These features can be used as descriptors of the objects resulting in an important data compression, because they can characterize the geometrical shape by a relatively small feature vector. Shape features can be grouped in two categories i.e. boundary features and region features. From the boundary of the image, the features extracted here are compactness, eccentricity, equivalent diameter, extent and solidity. These features are used for classification with neural networks. Table 1shows one sample feature values for each digit.

From the boundary of the image pixels, the features are computed as follows:

A. *Compactness*

Compactness of an image object is defined as the square of the objects perimeter to its area.

$$Compactness = \frac{Peremeter^2}{Area}$$

where the perimeter of the object is given the list of boundary coordinates. The perimeter of the object is given by $P = \sum_{i=1}^{n} d_i = \sum_{i=1}^{n} |x_i - x_{i+1}|$, where $x_1 \ldots x_n$ is the list of boundary coordinates

Area of the boundary image is the number of pixels in the region.

B. *Eccentricity*

Eccentricity is the ratio of the major axis to the minor axis. The major axis points are the two points in an image where the object is more elongated and where the straight line drawn between these two points is the longest. Major axis points are calculated by all possible combinations of perimeter pixels where the line is the longest.

$$Major\ Axis\ Length = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2}$$

where (x_1,y_1) and (x_2,y_2) are the coordinates of the two end points of the major axis.

The minor axis is drawn perpendicular to the major axis where the line has the maximum length.

$$Eccentricity = \frac{Minor\ Axis\ Length}{Major\ Axis\ Length}$$

C. Extent

Extent is defined as the ratio of the area of pixels in the region of the image to the area of pixels in the bounding box.

$$Extent = \frac{Area}{Bounding\ Box\ Area}$$

D. Equivalent Diameter

Equivalent diameter specifies the diameter of a circle with the same area as in the region of the boundary image.

$$Equivalent\ Diameter = \sqrt{\frac{4 \times Area}{\Pi}}$$

E. Solidity

Solidity is defined as the ratio of the area of the boundary to convex area of the image boundary.

$$Solidity = \frac{Area}{Convex\ Area}$$

IV. Classification using Probabilistic Neural Network

In Probabilistic Neural Networks when an input is existing, the first layer calculate the distances from input vector to the training input vectors and produces a vector whose elements indicates how close the input is to the training input. The second layer sums these values for each class of the inputs to produce as its net output a vector of probabilities. In second layer compete transfer function selects the maximum of these probabilities and produces an output '1' for that class and a '0' as an output for the other classes. The architecture of the neural network is shown in figure 3.

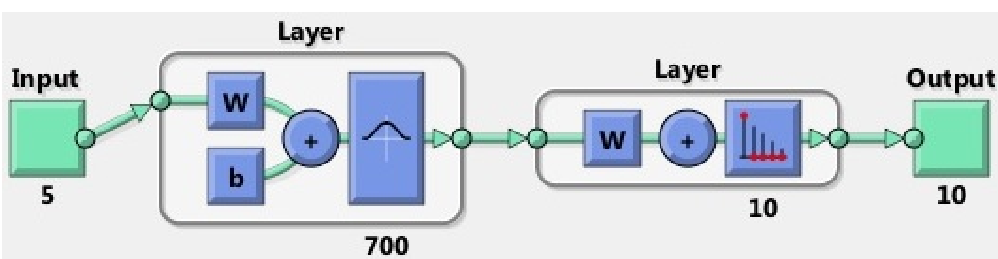

Figure 3. Probabilistic Neural Network (PNN) Architecture

V. Results and Discussions

70 samples are taken in the experiments conducted from each digit of 0 to 9 and a total of 700 samples of digit images from the MNIST handwritten digit database are taken. For these samples entire sample features are calculated and saved the result as an excel file. This excel file is given to the neural network as input to classify. Another input given to the neural network is a class label file. Out of 700 input samples 674 samples are classified correctly and 26 samples are misclassified. An error rate of 3.7% and a recognition rate of 96.3% are recognized and are shown in Table 2. The results are compared with different classifiers proved on this hand written numeral recognition problem with different feature extraction methods shown in Table 3.

VI. Conclusion

In this paper, a method to recognize handwritten digits from boundary descriptor properties is presented. A probabilistic neural network is used as a classifier to recognize the digit images. When the resolution of the character images grow larger, neural network training has a tendency to be slow due to further processing for larger input. If the character images have poor resolution, the training procedure is much faster. However, some important details might be lost. To resolve between resolution and training parameters, it has been shown that one can adopt the boundary descriptor feature vectors to train the network. Here the work done is limited to an isolated digit character. The extension of this work is to segment the numerical chain image which extracts the individual digits to be processed.

Table 1. Feature values of one sample for each digit.

Digit	Compactness	Eccentricity	Extent	Equivalent Diameter	Solidity
0	0.68	15.59	0.26	0.33	0.29
1	0.98	11.34	0.16	0.41	0.18
2	0.83	15.84	0.20	0.25	0.09
3	0.71	17.77	0.19	0.22	0.07
4	0.46	15.76	0.14	0.25	0.08
5	0.61	17.30	0.20	0.24	0.07
6	0.90	16.23	0.25	0.37	0.17
7	0.94	11.40	0.23	0.38	0.16
8	0.72	17.37	0.23	0.28	0.22
9	0.79	14.23	0.22	0.34	0.19

Table 2. Results

Digit	Correctly classified samples	Incorrectly classified samples	% Classification	% Misclassification
0	69	1	98.6	1.4
1	68	2	97.1	2.9
2	69	1	98.6	1.4
3	67	3	95.7	4.3
4	69	1	98.6	1.4
5	65	5	92.9	7.1
6	67	3	95.7	4.3
7	66	4	94.3	5.7
8	66	4	94.3	5.7
9	68	2	97.1	2.9
Total	**674**	**26**	**96.3**	**3.7**

Table 3. Comparison of Results of different methods.

Method	% Recognition rate	% Error rate
Kannada & Tamil Numerals [15]	93 & 90	7 & 10
Geometrical Features [14]	95.80	4.20
Vector quantization [16]	96.7	3.3
Morphological Features with MLP [13]	97.75	2.25
Author's method	96.3	3.7

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