Recognition of Characters and Patterns using Neural Network

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Abstract- This paper describes the recognition of handwritten characters using Probabilistic neutral network classifier. Identification of hand written characters requires the large number of data sets. The individual characters are identified using Segmentation and the feature analysis is done through the grey-level co-occurrence matrix. Finally the PNN Classifier is used to classify the each individual characters based on the stored data set.

Keywords- *GLCM-Grey Level Co-occurrence Matrix, PNN-Probabilistic Neural Network*

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1. INTRODUCTION

Now a days the data become the valuable asset in every field. In Olden days these data are available as the large number of files and registers. The drawback of these files is difficult to retrieve any needed data and it requires large effort in maintaining those data. As the technology emerges the computer plays a vital role in every fields. So there is a need to digitalize those data. Manually typing those large number of data requires much manual effort. Therefore handwritten recognition came in to exist. Recognition is not so easy for the artificial device. Because it requires large number of pre-processed instructions and data sets. In humans, recognition is done by the neurons present in the brain. Now in these artificial devices we are going to develop the artificial neural network to achieve the recognition. Recognition needs to be accurate and the error rate should be less.

The complexity for the recognition is the image background and the difficult text strokes. Therefore before moving in to recognition the image needs to be pre-processed and needs to be enhanced for further processing. The colour in the image makes difficult to process the image thus the colour needs to be removed. Therefore the image is converted to greyscale for processing. Secondly the image needs to be resized in to standard size so that the image can be processed well. Now the quality of the image should be improved so that the character in the image can be identified. It includes correcting the brightness level. Finally the segmentation should be done in the image so that each individual characters can be identified.

Second major step in the Hand written recognition is the Feature extraction. It is nothing but removing the unwanted portions of the image which is not required for recognition. It is also termed as highlighting the important features which is required for recognition. There are several feature extraction techniques, they include

1) Histogram of Oriented Gradients (HOG)
2) Local Binary Pattern (LBP)
3) Grey Level Co-occurrence Matrix (GLCM)

The Histogram of Oriented Gradients is used to detect the objects in the image by finding the histogram of gradient directions. First the image is divided in to cells and for the each pixel in the cell the edge direction is compiled. Second method is Local Binary Pattern, here also we divide the image in to cells and for each pixel in the cells we compute a local binary pattern. To compute a local binary pattern we compare a grey value with its neighbours. Third method is Grey Level Co-occurrence Matrix. Co-occurrence matrix in an image is defined as a Co-occurring values at a given offset. The GLCM is computed from the grey-scale image. The direction of analysis for GLCM can be horizontal, vertical or diagonal.After the computation of GLCM the features such as contrast, correlation, energy and homogeneity can be derived.

Final major step in the handwritten recognition system is the selection of artificial neural network which can be used for classification and recognition. Artificial Neural Network consists of set of interconnected nodes. Nodes are organised as input, hidden, and output. The input node consists of records of values which are input to the next layer of neurons. Then the values are processed and finally it is given in to the output nodes and the record is assigned to the class node with highest value.

2. PROPOSED SYSTEM

In the proposed system, we use the typical approach in the recognition the steps are shown in the fig 1.

2.1 INPUT IMAGE

The system uses a scanned image as an input image. The image is obtained using the scanner and it can be in the format such as jpg, or bmp.

2.2 PREPROCESSING

The pre-processing is done to enhance the image so that it can be easy for further processing. The first step in pre-processing is the conversion of image into grayscale. Because grayscale images are better for retrieving the values and also easy for processing.

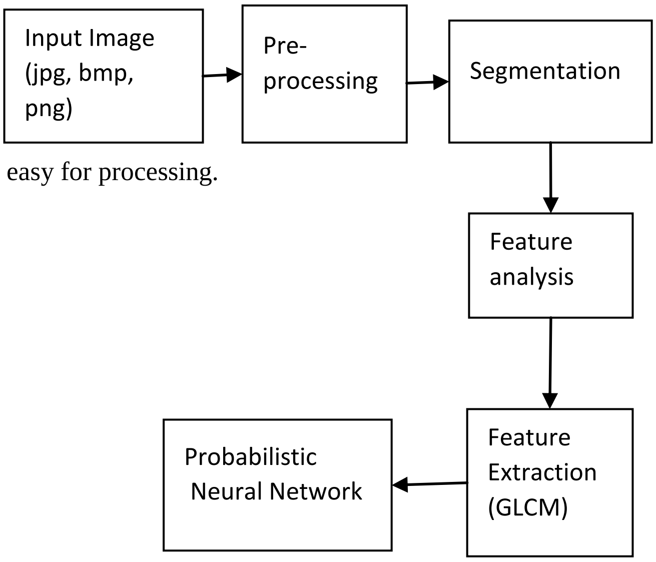

Fig 1: Block diagram of character recognition

Next the image is resized into standard size. So that every part of the image will be covered effectively.

Then the image brightness level should be checked. When the value of brightness is high then the value should be reduced. If it is low, then the brightness value should be enhanced.

2.3 SEGMENTATION

Segmentation is used to partition the image so that each pixel in the image can be identified easily. Segmentation is done to identify the edges and boundary of the objects.

Segmentation is carried out in two steps, they include edge detection and thresholding. Based on the intensity at the region boundaries the edges are identified. Thresholding is the simplest technique of segmentation. Here the threshold value is computed by using some techniques such as k-means clustering or maximum entropy method based on the threshold value the image is segmented.

Fig 2-Pre-processing

3. FEATURE EXTRACTION AND ANALYSIS

In this paper we propose the technique called grey level co-occurrence matrix. Grey level co-occurrence matrix represents the distance and spatial relationship over an image. The glcm is usually created from the grey scale image and the direction of analysis can be horizontal, vertical or diagonal.

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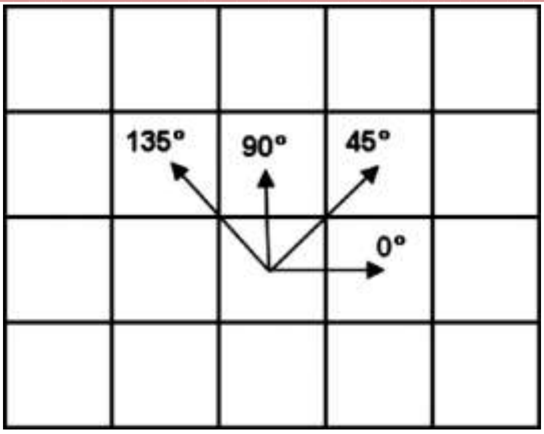


Fig 3- Directional analysis

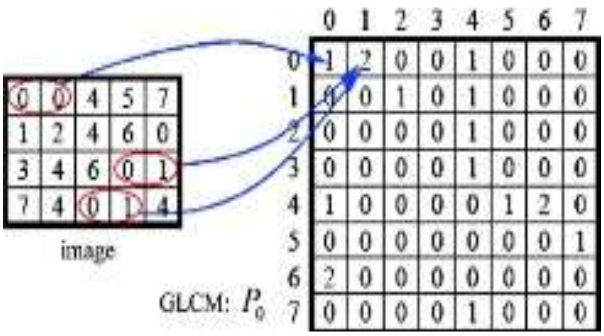


Fig 4- Example Image

After computing the grey level co-occurrence matrix the features such as contrast, energy, and homogeneity can be computed.

$$\text{Contrast} = \sum_{i,j} (i-j)^2\, p[i,j]$$

$$\text{Energy} = \sum_{i,j} p^2[i,j]$$

$$\text{Homogeneity} = \sum_{i,j} \frac{p[i,j]}{1+|i-j|}$$

$$\text{Entropy}: -\sum_{i,j} P(i,j)\log P(i,j)$$

$$\text{Correlation}: -\sum_{i,j} \frac{(i-\mu)(j-\mu)}{\sigma^2} P(i,j)$$

$$\text{Shade}: \sum_{i,j} (i+j-2\mu)^3 P(i,j)$$

$$\text{Prominence}: \sum_{i,j} (i+j-2\mu)^4 P(i,j)$$

$$\text{Variance}: \sum_{i,j} (i-\mu)^2 P(i,j)$$

Where,

$$\mu = \mu_x = \mu_y = \sum_i i \sum_j P(i,j) = \sum_j j \sum_i P(i,j) \text{ and}$$

$$\sigma = \Sigma_i (i-\mu_x)^2 \Sigma_j P(i,j) = \Sigma_j (j-\mu_y)^2 \Sigma P(i,j)$$

The contrast in GLCM measures the variance in grayscale levels across the image, whereas homogeneity measures the similarity of grayscale levels across the image. Thereby, the larger the changes in grayscale, the higher the GLCM contrast and the lower the GLCM homogeneity. Finally, GLCM energy measures the overall probability of having distinctive grayscale patterns in the image.

Brightness: Given an image I(x, y), we defined brightness as its average grayscale value:

$$c_{mean} = \frac{1}{n^2}\sum_{x=1}^{n}\sum_{y=1}^{n} I(x,y)$$

Size: To represent the size of an image, we counted the number of pixels above a threshold T (T = 157):

$$p = \sum_x \sum_y B(x,y); \;\; where \;\; B(x,y) = \begin{cases} 0 & I(x,y) < T \\ 1 & I(x,y) \geq T \end{cases}$$

Contour: In order to extract contour features, we first threshold the image to identify foreground pixels; the threshold was set to 0.95 times the largest pixel value in the image. Then, we identified the outermost pixel relative to the centre of mass of the foreground in angular increments of about 1 degree, and store the distance between center mass and radically-spaced outermost pixels in a 360-dimensional feature vector.

Finally, we employed principal component analysis called PCA to identify the directions of maximum variance in the 360-dimensional contour vector.

4. NEURAL NETWORK CLASSIFIER

In this paper we are going to use the probabilistic neural network classifier. Probabilistic Neural Network (PNN) is a multilayer perceptron feedforward network. It has four layers namely input, hidden, pattern and decision layers.

a) Input layer:

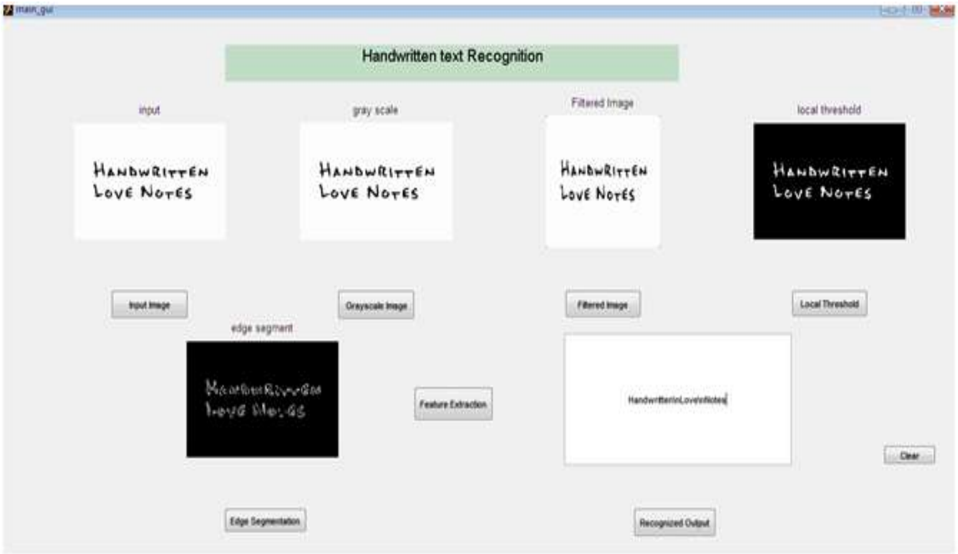
Before feeding in to the input layer the values are standardised, so that the range of values is in between -1 to +1. The input layer receives this value and distributes the constant value say 1.0 to the next layer called hidden node.

b) Hidden layer:

In this layer, the Euclidean distance is calculated from the neuron centre point and then RBF-Kernel function is applied. Finally the resulting value is passed to the pattern layer.

c) Pattern layer:

Pattern layer consists of pattern neuron and the actual target class in the hidden node and the weighted values from the neuron is passed into this pattern neuron. Pattern neuron just add the values of the class it represents. Which is useful in selecting the highest value.



d) Decision layer:

For each target category the weighted values are compared in this layer and the highest value is selected to predict the target category.

PNN is basically a classifier it maps an input pattern to a number of classification. It follows an approach called Bayesian classifier which is used in statistics. It is usually chosen because of its high training speed when compared to the other networks. The training and running procedure was implemented using matrix manipulation. The PNN is also based on the estimation of probability density function (pdf). It is based on the Parzen window pdf estimator. First the probability density function is calculated followed by the classification decision of parzen window classifier. The classifier decision is expressed as

$$p_k f_k > p_j f_j$$

Wherepk is the prior probability of occurrence and $f_k$is the estimated pdf.

The ProbabilisticNeural Network works by creating a set of multivariate probability densities which is derived from the training vectors that are presented to the network. The unknown input category is propagated to the pattern layer. After every node in the pattern layer receives the input the output of the node will be computed.

$$\pi_i^c = \frac{1}{(2\pi)^{n/2}\sigma^n}\exp\left[-\frac{(x-x_{ij})^T(x-x_{ij})}{2\sigma^2}\right]$$

Where*d* is the number of features of the input instance x, σ will be the smoothing parameter, and x_{ij} is a training instance to the category *c*. The summation layer compute the maximum likelihood of pattern *x*which is classified into *c* by summarizing and averaging the output neurons of same class.

$$p_i(x) = \frac{1}{(2\pi)^{n/2}\sigma^n}\frac{1}{N_i}\sum_{i=1}^{N_i}\exp\left[-\frac{(x-x_{ij})^T(x-x_{ij})}{2\sigma^2}\right]$$

Here $N_i$denotes the total number of samples in class *c*.

If *prior* probabilities for each class are same, and also the losses associated with making an incorrect decision is same, the decision layer unit classifies the pattern *x*from the Bayes's decision rule based on the output of all the summation layer neurons

C(x) = argmax {pi(x)}, i = 1,2,...,c

Here C(x) denotes the estimated class of the pattern *x* and *m* is the total number of classes in the training samples.

If prior probabilities for each class are different, and the losses associated with making an incorrect decision are also different, the output of all the summation layer neurons will be

C(x) = argmax {p_i(x) $cost_i$(x) $apro_i$(x)}, i = 1,2,...,c

Here $cost_i$(x) is the cost associated with misclassifying the input vector and $apro_i$(x) is the prior probability of occurrence of patterns in class *c*.

CONCLUSION:

The recognition of handwritten characters is achieved using the PNN classifier where GLCM techniques are used in the feature extraction. Since the PNN classifier is used the training speed is increased and the system can be used well when large number of data sets is trained.

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