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Offline Handwritten Character Recognition Using ANN and Diagonal Based Feature Extraction Technique

Ashok Kumar
M.tech, GJUS&T,
Hisar, India

Lalit Kumar
M.tech, KUK, Kurukshetra,
Haryana, India

Preeti
M.tech, KUK, Kurukshetra,
Haryana, India

Abstract— Character recognition techniques help in recognizing the characters written on paper documents and converting it in digital form. Character recognition is gaining interest and importance in the modern world due to its application in various fields. Handwritten character recognition is a very difficult problem due to great variation of writing style, different size and shape of the character. Accuracy and efficiency are the major parameters in the field of handwritten character recognition. Various feature extraction and training techniques are available for handwritten character recognition systems in the literature, each with its own superiorities and weaknesses. Feature extraction plays an important role in reducing the neural network training time. In this work an extension to diagonal based feature extraction scheme is proposed which is anticipated to be yielding better results as compare to the conventional schemes used for feature extraction.

Keywords- Offline handwritten character, neural network, feature extraction, segmentation

I. INTRODUCTION

Handwriting recognition has been one of the most fascinating and challenging research areas in the field of image processing and pattern recognition. Recognizing characters, letters or digits for human beings is not a big task. It can even be done by small child, but doing the same with machine is a difficult task [1].

Machine simulation of human functions has been a very challenging research area since the advent of digital computers. Machine simulation has been the subject of intensive research for the last three decades, yet it is still far from the final frontier [2].

Based upon the technique how the input data is obtained handwritten character recognition can be classified into two categories: Offline Handwritten character recognition and Online Handwritten character recognition. Recognizing handwriting recorded with a digitizer as a time sequence of pen co ordinates is known as online character reorganization. Off-line handwritten character recognition deals with the scanned handwritten document.

Stages involved in handwritten character recognition are: Preprocessing, segmentation, feature extraction and neural network (classification). Pre-processing aims to extract the relevant information and prepares that information for segmentation and recognition. In the segmentation, the input image is segmented into individual character and then, characters are resized into m x n pixels towards the training network to classify the character.

Neural network has a wide application in the field of pattern recognition. This work emphasizes on offline handwritten character recognition. In this work, English handwritten characters and digits are recognized through Feed Forward Multi-Layer Perceptron Network (MLPN) with one hidden layer. Back-propagation algorithm has been used to train the neural network. The network can be used to learn the character in the format of patterns and then trained network is simulated for recognizing the character that is presented in the form of image.

M. D. Garris et al [3] proposed a neural network based technique for handwritten digit recognition which yielded a writer-independent recognition rate of 92% and reduced substitutional errors to 2.2%.

R. Plamondon et al [4] described the nature of handwritten language, how it is transformed into electronic data, and the basic concepts behind written language recognition algorithms. Both the online case and the off-line case were considered.

G. Lera et al [5] described the use of Levenberg-Marquardt algorithm for training multi-layer feed forward neural networks. Though, the training time required strongly depends on neighborhood size. It is shown that, by performing an LM step on a single neighborhood at each training iteration, not only significantly saves the memory occupation and computing effort, but also, the overall performance of the LM method can be increased.

Satish Kumar et al [6] proposed a Zernike moment feature based approach for Devnagari handwritten character recognition. They used an artificial neural network for classification.

Normalization co-operated gradient feature [7] for handwritten Japanese and Chinese character recognition, which reduces the recognition error rate by factors ranging from 8.63 percent to 14.97 percent with high confidence of significance when combined with pseudo-two-dimensional normalization methods.

Ján Dolinský et al [8] defined the naturalness of handwritten characters. With this definition, the relationship between the font and its naturalness using canonical correlation analysis (CCA), multiple linear regression analysis, feed forward neural networks (FFNNs) with sliding windows, and recurrent neural networks (RNNs) was analyzed mathematically.

II. SYSTEM DESIGN FOR OFFLINE HANDWRITTEN CHARACTER RECOGNITION

Stages involved in offline handwritten character recognition are described in Figure 1. There are five major stages in offline handwritten character recognition: Image scanning, preprocessing, segmentation, feature extraction, Neural network (classification).

A. Image Scanning

In image scanning recognition system acquires a scanned image as an input image through a digital scanner or any other suitable digital input device. The input captured may be in gray, color or binary from scanner or digital camera. This image should have a specific format such as JPEG, BMP etc. [17].

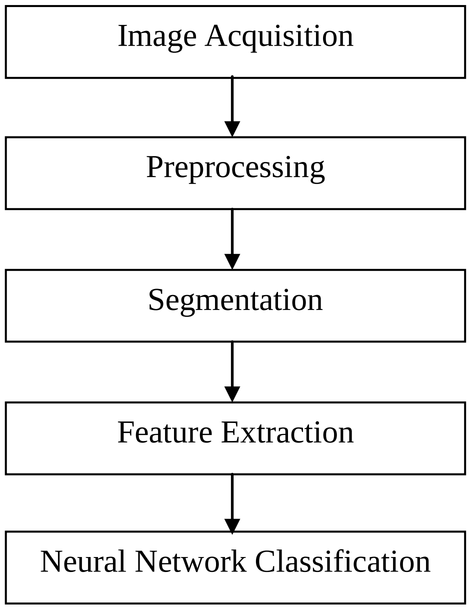

Fig. 1 Stages in offline handwritten character recognition

B. Preprocessing

The output of the image acquisition is fed as input to the preprocessing step. The raw data of handwritten characters will be subjected to a number of preprocessing steps to make it useable for the next steps. The preprocessing phase aims to extract the relevant textual parts and prepares them for segmentation and recognition. Pre-processing of the image means applying a number of procedures for thresholding, smoothing, filtering, resizing, and normalizing so that successive algorithm to final classification can be made simple and more accurate [18].

C. Segmentation

An image is present in the form of sequence of characters that is decomposed into sub-images of individual character in the segmentation stage. In this system, labeling process is used for segmentation of pre-processed input image into isolated characters by assigning a number to each character. This labeling provides information about number of characters in the image [9].

D. Feature Extraction

Each character has its own differential features, which play an important role in pattern recognition. Feature extraction describes the relevant shape information contained in a pattern so that the task of classifying the pattern is made easy by a formal procedure. The main goal of feature extraction is to obtain the most relevant information from the original data and represent that information in a lower dimensionality space. When the input data to an algorithm is too large and also may be redundant (much data, but not much information) then the input data will be transformed into a reduced representation set of features (also named features vector). A term feature extraction is termed that transforms the input data into the set of features. The features set will be used to extract the relevant information from the input data in order to perform the desired task using this reduced representation instead of the full size input. Feature extraction method used in this work is Diagonal Based feature extraction [10, 15].

The widely used feature extraction schemes are Template matching, Gradient feature extraction method, Directional feature extraction, Fourier descriptor, Zoning, Diagonal Based Feature Extraction.

1.) Conventional Feature Extraction: In conventional scheme, if a line passes through a pixel, then the value of the corresponding pixel will be set one (1), otherwise it is taken as zero (0). In this scheme the number of inputs are m x n=mn, m x n is the size of the input image, which requires more time to learn and classify the characters.

2.) Gradient Based Feature Extraction: In this feature extraction scheme Sobel's mask is applied to calculate the horizontal gradient (gx) and vertical gradient (gy) components as shown in Figure2 [12].

1	2	1
0	0	0
-1	-2	-1

Horizontal component

-1	0	1
-2	0	2
-1	0	1

Vertical component

Fig. 2 Sobel's Operator

The gradients of a pixel (i,j) are calculated by using following formula.

Gx = gv (i, j) = f (i − 1, j + 1) + 2f(i, j + 1) + f (i + 1, j + 1)

−f(i − 1, j − 1) − 2f(i, j − 1) − f(i + 1, j − 1)**………(1)**

Gy = gh (i, j) = f (i − 1, j − 1) + 2f(i − 1, j) + f (i − 1, j + 1)

−f (i + 1, j − 1) − 2f(i + 1, j) − f(i + 1, j +1) **…………….(2)**

grad = Gy/ Gx = tan-1[gh(i,j) / gv(i,j)]

In this scheme, the handwritten characters are converted into the gradient values ranging between 0 to 6.28. It is assumed that gradient values will be taken -1whenever a pixel is surrounded by all black pixels.

3.) Directional Features: After computing the gradient of each pixel of the character, In this scheme gradient values are mapped into 12 direction values with angle span of 30 degree between any two adjacent direction values. The orientations of these 12 directional values are shown in Figure 3 [19].
The formula to calculate the mapping of the Gradient values into 12 direction values is-.
Direction [n(i,j)] =(30(n-1) °)≤ grad(i,j) < (30n°)
The detail values of 12 direction features can be shown in Table I

Table I mapping of gradient on direction values

Gradient values (g)	Direction	Gradient values (g)	Direction
g = -1	0	π < g <=7 π/6	7
0 <= g <= π/6	1	7π/6 < g <=4 π/3	8
π/6<g < = π/3	2	4π/3 < g <=3 π/2	9
π/3< g <= π/2	3	3π/2 < g <=5 π/3	10
π/2 < g <=2 π/3	4	5π/3 < g <=11 π/6	11
2π/3 < g <=5 π/6	5	11π/6 < g <=2 π	12
5 π/6 < g <= π	6	--	--

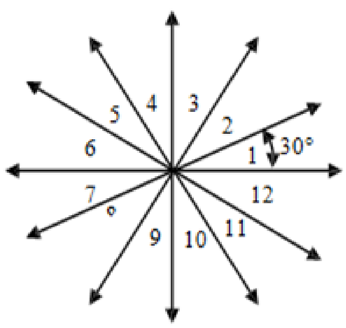

Fig. 3 Orientation of Direction

These mn direction values for m x n pixels are input to the neural network where the value of each direction is between 1 to 12.If a pixel is surrounded by all the pixels having values zero then is its gradient assigned as 1. During the calculation of directional feature if gradient values are -1 then its directional feature values are assigned the valueszeros(0s).

4.) Diagonal Based Feature Extraction: In this feature extraction scheme. every character image having size m x n pixels is divided into m x n/p x q equal zones, each of size p x q pixels (Fig.4(c)).In this figure, the image size is taken as 90 x 60 pixels and zone size is 10 x 10 pixels so the number of zones is equal to 54. The features are extracted from each zone pixels by moving along the diagonals of its respective 10X10 pixels. The single sub-feature is obtained from each zone which contains 19 diagonal lines and the foreground pixels present long each diagonal line by summing all the values, thus 19 sub-features are obtained from the each zone. In the extended work of this feature extraction schemes, sub features are extracted diagonally from both side left to right and right to left. So the number of sub feature extracted increased from 19 to 38.The average of these 38 sub-features values are used to form a single feature value and placed in the corresponding zone (Fig. 4 (b)). This process is sequentially repeated for all m x n/p x q zones present in the image. There can be some zones whose diagonals values are empty for foreground pixels. The feature values are zero for these corresponding zones. Finally, 54 extracted features are obtained for each character. In addition, 9 and 6 features are obtained by averaging the values placed in zones row wise and column wise, respectively. As result, every character is represented by 69, that is, 54 +15 features [20].

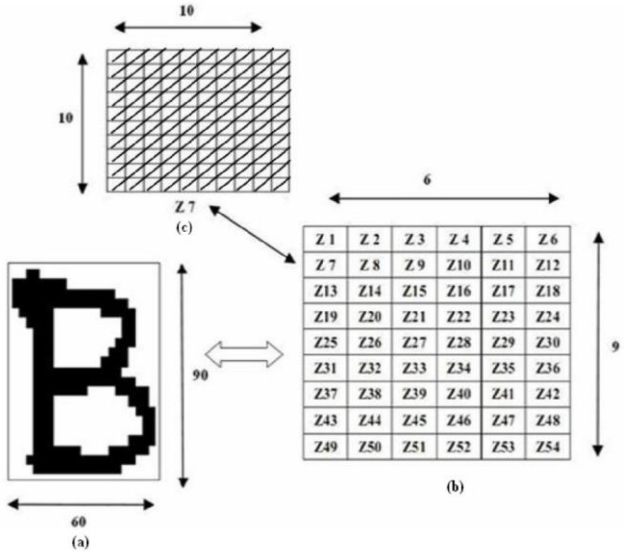

Fig. 4 Diagonal Based Feature Extraction

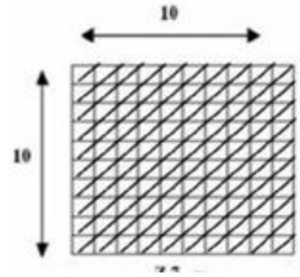

Fig. 5 Extended Diagonal Based Feature Extraction

The recognition accuracy and efficiency heavily depends on the feature extraction scheme used in the handwritten recognition system. In this review work the extension to the diagonal based feature extraction method proposed which uses the average feature value of the 38 sub-feature values. As every character is represented as 69 features so it gives the better recognition accuracy and efficiency. This recognition system is eminently suitable for many applications including, bank processing, document reading, postal address recognition, parcel address recognition and to convert of any handwritten document into structural text form. This work can be further extended for special character recognition and other languages

E. Neural Network

Neural network is used for classification of the character. We first create the neural network, then we train the network with training data and then we simulate the network with test data.

1.)Network Creation: A feed-forward back propagation network is created. To create a feed forward network, newff() function is used.

net = newff(Input, target, h_i, TF, BTF);
Newff function returns the network object. This function takes many other arguments.
First argument is matrix(R x Q) of Q sample R-element input vectors.
Second argument is m x n matrix of n sample m-element target vectors.
Third argument h_i specifies the size of the i^{th} hidden layer. TF specifies the transfer function and BTF is back propagation training function.
If only three arguments are used then the default transfer function for hidden layers is tansig() and the default for the output layer is purelin(). Trainlm() is the default training function. Newff() command creates the network object and also initializes the weights and biases of the network; therefore the network is ready for training**.**

- ***Reinitielising the weights and biases***

Firstly, weights and biases are initialized after that feed forward network is trained. The newff command automatically initializes the weights. The weights can be reinitialized. Init() function is used to reinitialize the weights. This function takes a network object as input and returns a network object with all weights and biases initialized. A network can be initialized (or reinitialized) by using:
net = init(net);

2.) Network Training: After initialization of the weights and biases training of the neural network takes place. The features extracted from the second step would serve as the data to train the neural network. Recognition of handwritten characters is a very complex problem. The capability of neural network to generalize and insensitive to the missing data would be very beneficial in recognizing handwritten characters. In this paper, for offline handwritten character recognition Feed Forward Multi-Layer Perceptron network (MLPN) with one hidden layer has been used. For training, back-propagation algorithm has been implemented. [11]

III. CONCLUSION

The recognition accuracy and efficiency heavily depends on the feature extraction scheme used in the handwritten recognition system. In this review work the extension to the diagonal based feature extraction method proposed which uses the average feature value of the 38 sub-feature values. As every character is represented as 69 features so it gives the better recognition accuracy and efficiency. Scanned written document is preprocessed and then relevant features are extracted. These features act as input to train the neural network. After training the neural network is simulated for offline handwritten character recognition. System becomes adaptive if it learns the different pattern of same character under the same label.

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