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TECHNICAL NOTE

Neural Network Based Recognition System Integrating Feature Extraction and Classification for English Handwritten

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A R T I C L E   I N F O

A B S T R A C T

Handwriting recognition has been one of the active and challenging research areas in the field of image processing and pattern recognition. It has numerous applications that includes, reading aid for blind, bank cheques and conversion of any hand written document into structural text form. Neural Network (NN) with its inherent learning ability offers promising solutions for handwritten character recognition. This paper identifies the most suitable NN for the design of hand written English character recognition system. Different Neural Network (NN) topologies namely, back propagation neural network, nearest neighbour network and radial basis function network are built to classify the characters. All the NN based Recognition systems use the same training data set and are trained for the same target mean square error. Two hundred different character data sets for each of the 26 English characters are used to train the networks. The performance of the recognition systems is compared extensively using test data to draw the major conclusions of this paper.

1. INTRODUCTION

Handwriting Character Recognition (HCR) has been quite a fascinating and challenging research area in field of image processing and pattern recognition. It contributes immensely to the advancement of automation process and improving the interface between man and machine in numerous applications. Several research works have been focusing on different methodologies in an attempt to reduce the processing time while simultaneously improving recognition accuracy [1,2].

In general, handwriting recognition can be classified into two major categories, namely off-line and on-line handwriting recognition methods. In the off-line recognition, the writing is usually captured optically using a scanner and the completed writing is available as an image. In the on-line system, the two dimensional coordinates of successive points are represented as a function of time and the order of strokes made by the writer are also available. The on-line methods have been shown to be superior to their off-line counterparts in recognizing handwritten characters due to the temporal information available with the former [3].

Off-line handwriting recognition is comparatively a difficult task, as different people exhibit different handwriting styles. Optical Character Recognition (OCR)/Image Character Recognition (ICR)engines have been primarily developed for recognizing machine printed and hand printed texts, while the recognition of handwritten documents entails special consideration as it involves recognizing the characters written with varying styles.

The steps in any handwritten recognition system are pre-processing followed by segmentation, feature extraction and classification. Pre-processing shapes the input image into a form suitable for segmentation [4]. This includes filtering, morphological operations, noise modelling and normalization. In the segmentation, the input image is segmented into individual characters and then, each character is resized into m x n pixels towards the training network. Segmentation includes external and internal segmentation. External segmentation decomposes page layout into logical units. while internal segmentation decomposes words into characters.

Feature extraction is a method widely used in pattern recognition. Feature extraction determines the important

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properties such as Aspect Ratio, Percent of pixels above horizontal half point, Percent of pixels to right of vertical half point, Number of strokes and Average distance from image centre. This approach provides the recognizer more control over the properties used in identification. However, certain methods of modelling can incorporate both the feature extraction and classification stages together for simplifying the process of recognition. Such methods include the Hidden Markov models and Artificial Neural networks.

Hidden Markov models (HMM) are especially known for their application in handwriting and gesture recognition. A hidden Markov model can be considered as a generalization of a mixture models where the hidden variables, which control the mixture component to be selected for each observation, are related through a Markov process rather than independent of each other. Extraction and recognition of handwritten alphanumeric characters from application forms using discrete hidden Markov models is reported in [5]. The system recognizes 60 alphanumeric characters (26 English upper-case letters, 24 Greek upper-case letters and 10 numerals). The experiments carried out have yielded recognition rates of 93% in character level and 88% in word level. The latter improved to 97% by lexical confirmation. Multi HMM can also be used. Alceu de Britto *et al* [6] proposed an approach for recognizing the handwritten numeral strings that relies on the two-stage HMM-based method. HMM suffer from intrinsic limitations, mainly due to their arbitrary parametric assumption. Artificial neural networks (ANNs) appear to be a promising alternative in this respect.

Neural network recognizers learn from an initial image training set. The trained network then performs the character identification. Each neural network uniquely learns the properties that differentiate training images. It then looks for similar properties in the target image to be identified. Neural networks are quick to setup; however, they can be inaccurate if the learning is incomplete or if the system has over learnt unimportant data in the target. Yet any system using this approach requires substantially less development time than a feature extraction based network or a HMM based method.

The artificial neural network as the backend for performing classification and recognition tasks using segmented images have been reported in literature. The architecture of the neural network to a large extent determines the capability for classification. The popular methods are Template matching, feed forward networks, nearest neighbourhood method and radial basis network. The methods reported in literature include single layer networks, multilayer networks and use of multiple neural network structures.

A back proagation NN with single hidden layer is proposed by Said *et al* [7]. The proposed method optimizes the number of neurons in the hidden layer independent of the intial value.

Multilayer Feedforward networks were used by Saleh Ali K. Al-Omari *et al* [8]. They proposed two different architectures namely 600-50-10 with one hidden layer and 600-250-6-10 with two hidden layers for recognizing the handwritten isolated Arabic digits using neural networks. The network uses 1000 digits for training using back propagation algorithm. These studies were conducted on the Arabic handwritten digits of 10 independent writers who contributed a total of 1300 Arabic digits, divided into two data sets. The two hidden layer network performs better with an overall accuracy of 95% on the test data set of 300 digits.

The effect of activation function on a feed-forward NN based recognition system has been studied and presented in [9]. For sample creation, 250 numerals were collected from 35 people. After binarization, these numerals were clubbed together to form training patterns for the neural network. Experiments were conducted by selecting different combinations of two activation functions out of the three activation functions namely logsigmoid, tansigmoid and purelinear. The results revealed that the percentage recognition accuracy of the neural classifier was observed to be optimum when tansigmoid activation functions are used for hidden and output layers.

Multiple Neural Network models are also reported in the literature. In paper [10], multiple neural network models are used to recognize the Kannada language characters and the period during which the script was written. This involves two phases. The first phase of the work incorporates an Artificial Neural Network for identifying the base character. The second phase consists of a Probabilistic Neural Network model designed for the identification of age pertaining to the base character. Characters dated from century BC to the present day are used for analysis and experimentation results. Another multiple Neural Network approach to recognize a manually typed cheque amount was proposed in [11]. It employs a group of four neural networks of different types that are applied in parallel to reduce the chances of incorrect readings and the digits are classified. The overall accuracy using Multi Layered perceptron (MLP) neural network is 85%.

In this paper, an off-line handwritten character recognition system using neural networks that integrate both feature extraction and classification processes is investigated. Prior to segmentation, the pre-processed image is converted into binary image. The binary image is segmented into individual characters and then, each character is resized into 30x20 pixels. Each resized character is classified and recognized using different neural classifiers. As the structure of the neural network determines the efficiency of the recognition system, this paper investigates and compares three types of neural

classifiers, namely, (i) Feed forward network, (ii) Radial basis network and (iii) Nearest neighbour network. Also, the simplest technique, namely, template matching is used for comparison. An extensive simulation study identifies the best possible network in terms of recognition accuracy and network complexity. The results obtained are presented and discussed.

The rest of the paper is organized as follows. In section II, introduction to handwritten recognition system is described. In section III, an integrated approach for feature extraction and classification is presented using neural network based classification and compared with convention template matching technique. The experimental results are presented in section IV, and the paper is concluded in section V.

2. HANDWRITTEN RECOGNITION SYSTEM

In this section, the proposed recognition system is described. A typical handwriting recognition system consists of pre-processing, segmentation, feature extraction, classification and post processing stages. The general schematic diagram of the recognition system is shown in Fig.1.The proposed method in which both the feature extraction and classification processes together are preformed in a single stage is shown in Fig.2.

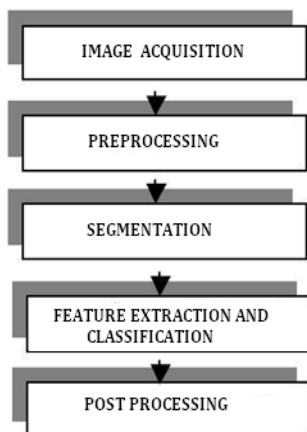**Figure 1**. General off-line character recognition system

Figure 2. Schematic diagram of the proposed off-line recognition system

2.1. Image Acquisition   In Image acquisition, the recognition system acquires a scanned image as an input

image. The image should have a specific format such as JPEG, BMP etc. This image is acquired through a scanner, digital camera or any other suitable digital input device. Data samples for the experiment have been collected from different individuals. Samples of the collected handwritten English characters A to Z are shown in Fig.3.

Figure 3. Samples of handwritten English characters A to Z

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2.2. Pre-processing   The pre-processing is a series of operations performed on the scanned input image. It essentially enhances the image, making it suitable for segmentation. The various tasks performed on the image in the pre-processing stage are shown in Fig. 4. Binarization process converts a gray scale image into a binary image using global thresholding technique. Detection of edges in the binarized image is done using sobel technique. Image dilation and filling of holes are performed in the last two stages to produce the   pre-processed image suitable for segmentation [12].

Figure 4. Pre-processing of handwritten character of image

2.3. Segmentation   In the segmentation stage, an image consisting of sequence of characters is decomposed into sub-images of individual character [13]. In the proposed system, the   pre-processed input image is segmented into isolated

characters and each character is assigned a number using a labelling process. This labelling provides information about number of characters in the image. Each individual character is uniformly resized into 30X20 pixels for classification and recognition stage.

2.4. Feature Extraction   The widely used feature extraction methods are Template matching, Deformable templates, Unitary Image transforms, Graph description, Projection Histograms, Contour profiles, Zoning, Geometric moment invariants, Zernike Moments, Spline curve approximation, Fourier descriptors, Gradient feature and Gabor features [14-16]. Due to the nature of handwriting with its high degree of variability and imprecision extracting these features, is a difficult task.

This paper does not adopt any of the above stated methods for feature extraction. The binary image is segmented into individual characters and then, each character is resized into 30x20 pixels. Each resized character is subjected to the classification and recognition tasks. That is, each resized character has 600 pixels and these pixels are taken as feature inputs to the different classifiers.

2.5. Classification   The classification stage is the decision making part of the recognition system. The 600 pixels derived from the resized character in the segmentation stage form the input to the classifier. In general the feature vector is denoted as X, and defined as $X = (f_1, f_2, \ldots, f_d)$, where f denotes features and d is the total number of pixels present in the each character. The number of input neurons is determined by length of the feature vector d. The total numbers of characters n determines the number of neurons in the output layer.

2.6. Post-processing   Post-processing stage is the final stage of the proposed recognition system. It prints the corresponding recognized characters in the structured text form by calculating equivalent ASCII value using recognition index of the test samples.

3. INTEGRATED APPROACH TO FEATURE EXTRACTION AND CLASSIFICATION

During the last few decades, the field of character recognition has received a major attention from research workers in diverse disciplines such as conversion of handwritten document to an editable soft format, recognition of postal addresses for automated postal system, data and word processing, data acquisition in bank checks and processing of archived institutional records. Some methods integrate the feature extraction and classification tasks. Such methods are simpler and easier to implement. In this paper such methods are studied and the accuracy achieved is reported.

3.1. Template Matching   Template matching is a simple and commonly used classification technique for character recognition. The unknown input character image is compared pixel-by-pixel with the templates of the recognizable characters. The character,whose template has the closest resemblance to the input image in terms of maximum pixel matching, is declared as the input character. In this paper, each test data was resized into an image of size 30x20 pixels. The printed character template (Times New Roman style) is saved in the database. No training is required. The test data was given as input and the recognition accuracy obtained is 54.27%. This method is simple, but recognition is poor as handwritting styles vary considerably among different people and some English characters have similar structures. Hence this method cannot be used in applications, which require high recognition rates [17].

3.2. Neural Network based classifier   Neural Network (NN) techniques offer a promising solution as classifiers in the handwritten character recognition system. The image after resizing is taken as an input. The classification capability of the network depends on the architecture and learning rule. The architectures considered in this paper are feed forward architecture [18-19], nearest neighbourhood [20] and radial basis function architecture [21]. To evaluate the performance of the proposed method the handwritten uppercase English alphabets were collected from different individual writers. Of the 7800 samples collected, 5200 samples were used for training purpose and remaining 2600 samples were used for testing. The proposed recognition system has been implemented using Matlab 7.1. The recognition systems were designed using different methods as listed below.

3.2.1 Feed Forward Back Propagation Neural Network classifier   The scanned image is taken as dataset/ input and feed forward architecture is used. As each image is resized into 30X20 pixels, the input layer has 600 neurons equal to the total number of pixels. The number of output neurons is based on the number of alphabets. As all the English alphabets are used, the output layer has 26 neurons. All the neurons use log-sigmoid transfer functions. The back propagation algorithm with momentum and adaptive learning rate is used to obtain the parameters of the network. Two Hundred different handwritten data sets were used for training the neural network. The number of hidden layers and the number of neurons in each layer are to be obtained through trial and error. Through numerous simulations it was identified that a maximum of two hidden layers and a maximum of 100 neurons in each hidden layer would be sufficient for character recognition. Further increase in the number of neurons did not considerably improve the accuracy. This feed

forward neural network architecture was trained for a target MSE of 10e-8. After the network is satisfactorily trained, the parameters of the trained network are fixed to enable testing.

The architecture of the three layer neural network for the handwritten recognition system is shown in Fig.5 and the network training parameters are shown in Table 1. The results obtained are shown in Table. 2.

TABLE 1. Feedforward Neural Network Training Parameters

Feedforward Neural Network parameters	
Input nodes	600
Hidden layers	2
Hidden layers nodes	100 each
Output nodes	26(alphabets)
Training epochs	50000
Training algorithm	Gradient descent with momentum training and adaptive learning
Performance function	Mean Square Error (MSE)
Training goal achieved	10e-8

TABLE 2. Performance Comparison of Different Classifiers

Number of training samples	5200 samples	
Number of testing samples	2600 samples	
Classifier	Number of correctly recognized alphabets	Recognition rate in %
Template Matching	1411	54.27
Feed Forward NN	2448	94.15
Nearest neighbour NN	2244	86.96
Radial basis function NN	2245	89.42

The feed forward neural architecture of the network with two hidden layers used for character recognition is illustrated in Fig. 5.
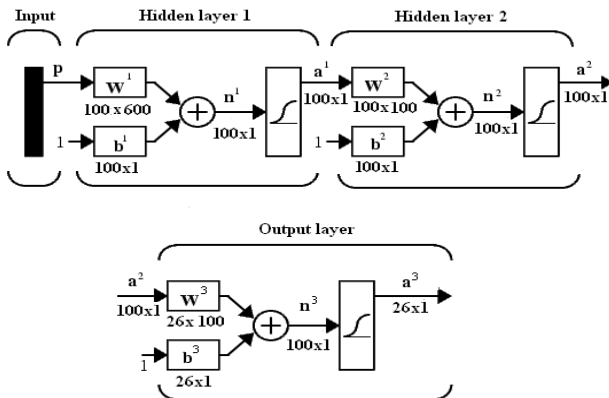

Figure 5. Two hidden layer neural network for character recognition

The output of the ith layer is defined by

$$a^i = \log sig(w^i a^{i-1} + b^i) \qquad (1)$$

where,
$a^0 = P$ and $i = [1, 2, 3]$,

w^i = Weight vector of ith layer

a^i = Output of ith layer

b^i = Bias vector for i^{th} layer

P = input vector for the network

3.2.2 Nearest Neighbour classifier   In pattern recognition, the k-nearest neighbour algorithm is used for classifying the characters based on neighbourhood in the feature space. Different types of Nearest Neighbour techniques have been reported in the literature [22]. The k-nearest neighbour technique using Euclidean distance method is used in this paper. The binary images are resized into 30x20 pixel images. Two hundred sets of each alphabet are used in the training phase. The training phase of the algorithm consists of storing the feature vectors with class labels of the training samples. A different data set consisting of 2600 samples is used for testing. The performance of kNN classifier is observed for different values of k ranging from 1 to 10. The Euclidean distances are computed between the test vectors to all the stored vectors. The computed distances are ranked in ascending order. The k nearest neighbours are chosen. The majority rule with the nearest point tie-break is used for classification.

Simulation results show that k = 4 yields good accuracy for recognizing the handwritten English alphabets. The results obtained for recognizing the handwritten English alphabets are summarized in Table.2.

3.2.3 Radial basis classifier   Radial basis function (RBF) networks is a good classifier and used for a wide range of applications [23]. It is a linear combination of radial basis functions. The RBF architecture used for character recognition is shown in Figure 6.

The total number of radial basis function neurons is 100. The output layer has 26 neurons corresponding to 26 English alphabets.
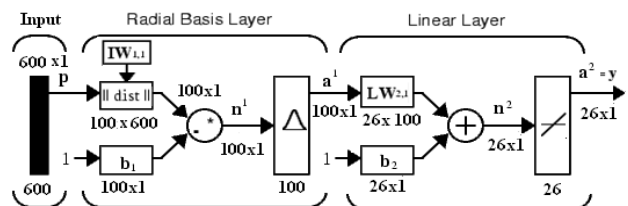

Figure 6. Radial basis function architecture for character recognition

The output of ith layer is given by

$$a_i^1 = radbas(\|IW_{i,i} - p_i\| b_i^1) \qquad (2)$$

$$a^2 = purelin(LW_{2,1}a^1 + b^2) \qquad (3)$$

Where,

$a_i^1 = i^{th}$ element of a^1

$_iIW_{1,1}$ is a vector made of the ith row of ith $IW_{1,1}$

The results obtained are summarized in Table 3.

TABLE 3. Summary of the results achieved by the proposed methods

Classifier	No of alphabets with recognition rate greater than 90%	Alphabets with a recognition rate greater than 90%
Template Matching	2	U, L
Feed Forward NN	23	A,B,C,F,G,I,J,K,L,M,N,O, P,Q,R,S,T,U,V,W,X,Y,Z
Nearest neighbour NN	8	C,D,L,O,P,T,U,W
Radial basis function NN	14	A,C,F,G,L,N,P,S,T,U,V,W, Y,Z

4. RESULTS AND DISCUSSION

The experimental results obtained in recognizing the handwritten English characters using four different classifiers are summarized in Table.2. The recognition accuracy obtained for the template matching method and the NN methods are also summarized in Table 2.
The results in Table 2 indicate the superior recognition accuracy of Feedforward Neural network as compared to other classifiers. Using a number of handwritten test data the confusion matrix was obtained for the four different classifiers. This was to investigate the recognition accuracy for each alphabet. This parameter is important as any written text would have a varied number of each alphabet. If the classifier has more than 90% recognition rate for each alphabet then the overall worst case recognition rate would be almost constant irrespective of the data.

Table 3 reports the number of alphabets having recognition rate less than 90% and the alphabets are also listed. It is seen from Table 3 that template matching has a poor recognition rate for 24 alphabets and hence has very poor recognition accuracy. Among the NN based classifiers the Feed forward neural network recognizes 23 alphabets with over 90% accuracy and is the best classifier.

The classification accuracy of the Feedforward NN is shown separately for each alphabet in Fig. 7. The

maximum number of misclassification occurs for the letter D which is misclassified 16 times for every 100 presentations (84% recognition). All the other alphabets have better recognition accuracy.
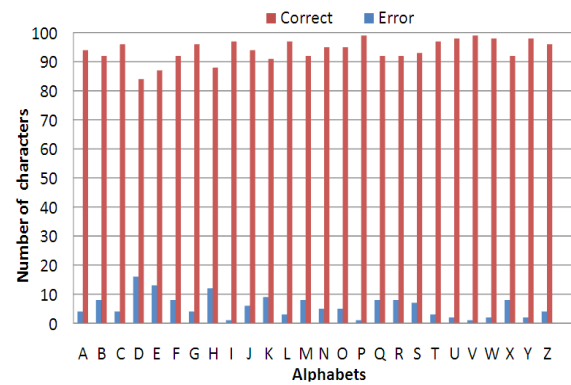

Figure 7. Performance illustration the correct & error individual alphabets for the Feed forward NN

5. CONCLUSIONS

An off-line handwritten character recognition system with four different classifiers namely, template matching, Feedforward NN, radial basis function NN and neatest neighbour NN for recognizing handwritten English alphabets has been described in this paper. The feature extraction and classification tasks are performed together as a single process in the proposed system unlike in typical handwritten recognition systems in which these tasks are carried out in two different stages. As a result, the proposed system is found to be less complex and allows faster recognition of characters. All the different classifiers have been trained with 200 sets of data and extensively tested. Experimental results show that the feed forward neural network is distinctly superior to the other classifiers in recognizing the handwritten English alphabets. Further investigation was carried out to identify the recognition rates for each letter of alphabet. This would help to estimate the recognition rate irrespective of the handwritten content. It was identified that the Feedforward NN outperformed the remaining classifiers. The proposed system will find useful applications in recognizing the handwritten names, reading documents and conversion of any handwritten document into structural text form. Further improvements may be possible with a more complex Feedforward NN architecture but this would also increase the computation complexity. Therefore, combination of a standard feature extraction technique with Feedforward NN may provide better solutions.

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A R T I C L E I N F O	چکیده

شناسایی دست خط یکی از حوزه‌های پژوهشی محرک و چالش برانگیز در زمینه پردازش تصویر و الگو شناسی بوده است. این حوزه دارای کاربردهای متعددی است که شامل کمکی برای خواندن برای افراد نابینا، چک های بانکی، و تبدیل هر نوع سند دست نوشته به فرم متن ساختاری است. شبکه های عصبی (NN) با توانایی یادگیری ذاتی خود راه حل های امیدوار کننده‌ای برای شناسایی کاراکترهای دست نوشته ها ارائه می دهد.این مقاله مناسب ترین NN را برای طراحی سیستم شناسایی کاراکتر انگلیسی نوشته شده با دست را شناسایی می‌کند. توپولوژی های مختلف شبکه های عصبی (NN) یعنی ، انتشاررو به عقب شبکه های عصبی، نزدیکترین شبکه همسایه وشبکه با پایه تابع شعاعی است برای طبقه بندی کاراکترها ساخته شده‌اند. تمامی سیستم های شناسایی مبتنی بر NN از مجموعه داده‌های اموزشی یکسانی استفاده نموده و برای رسیدن به متوسط مربع خطای یکسانی اموزش میبینند.دویست مجموعه کاراکتر مختلف هر یک از ۲٦ کاراکتر انگلیسی برای آموزش شبکه استفاده می شود.به منظور دریافت نتیجه نهایی از این مقاله عملکرد سیستم های شناسایی به صورت گسترده با استفاده از داده‌های تست مقایسه شده اند.