ISSN 2250-0987
Binod kumar Prasad, UNIASCIT, Vol 2 (3), 2012, 314-317

ZONE BASED FEATURE EXTRACTION METHOD APPLIED TO CHARACTER RECOGNITION

Binod Kumar Prasad

Department of Electronics and Communication Engineering,

Bengal College of Engineering and Technology, Durgapur, INDIA.

***Abstract*— Character recognition has attracted the attention of researchers since the early days of computing. Since then, a number of successful systems have been forwarded. In this paper, zonal feature extraction method has been utilized both globally and locally to recognise a character image.The aim of taking zonal features is to decrease algorithm complexity. However, the recognition tool is HMM. The overall recognition accuracy rate of 92.67% has been achieved.**

***Keywords*—Feature extraction, Zoning method, Handwritten character recognition, Viterbi algorithm, Baum-Welch algorithm.**

I. INTRODUCTION

Character recognition is nothing but Machine simulation of human reading [1], [2]. Study reveals that the methods of Character Recognition have grown up sequentially [3], [4]. Free handwritten recognition, without domain specific constraints and large vocabularies was addressed only recently in a few papers [5], [6]. The recognition rate of such system is still low and there is a need of improvement [7].

The feature extraction method consists of features from Zoning technique.

The zoning approach requires the spatial division of the character image where each division is termed as a zone and then a suitable feature extraction method is applied to individual zone to find the feature vector. The major advantage of this approach stems from its robustness to variations, ease of implementation and high recognition rate [8].Actually, these specialities tempted me to apply the zonal concept to off-line Handwritten Character Recognition (HCR).

In [8] M. Hanmandlu et al. have derived zone based distance feature by means of normalizing the sum of individual distances by the no. of pixels in the zone but in this paper normalization of the sum of individual distances of bright pixels has been done by the summed up distance of all the pixels in the respective zone only.

The method has been applied to a particular image in four ways-(1) by keeping the image in original form (2) by inverting the image laterally (3) by inverting the image vertically (4) by shearing the image horizontally in both positive and negative directions.

Features by means of zoning method have been extracted both globally and locally.

II. PROPOSED MODEL

Generally for each character, a single HMM model is considered and trained by feature vectors. But it is observed that some handwritten characters (e.g. A, W) show two completely different formats as shown in Fig.2. So, multiple HMM models have been used for these characters whereas for other characters, single HMM model is considered as shown in fig.3. Models are trained by the sequence of the symbols of the features extracted from some of the samples. To test a handwritten character image, we extract the similar features using same procedure as earlier and the corresponding sequence (observation) is compared with each HMM model .P(O/λ), probability of the observation sequence (O) by the models (λ) is compared and the highest probability concludes the highest matching of the features with the corresponding model.

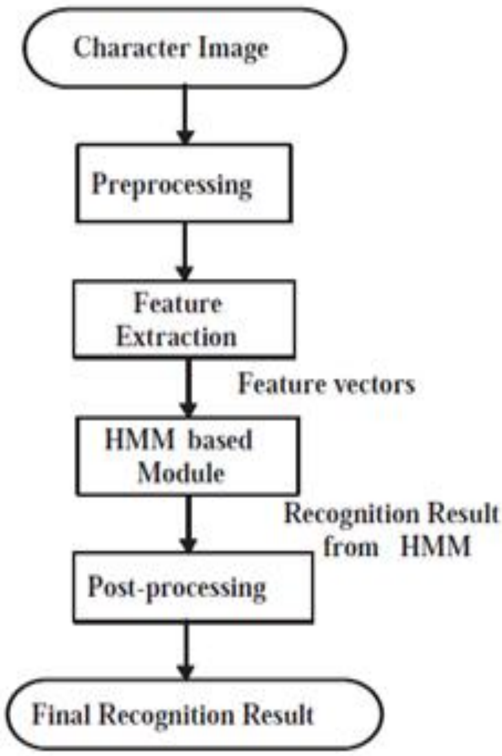


Fig. 1 System overview

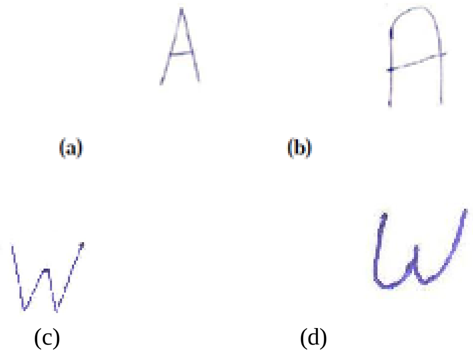


Fig.2 Two completely different formats for handwritten character A (a) A1 (b) A2 and for character W (c) W1 (d) W2

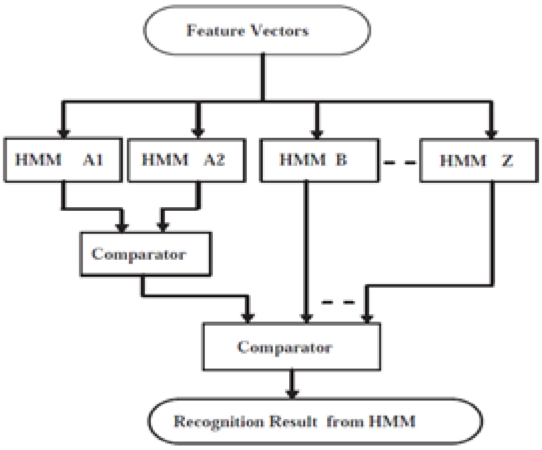


Fig.3 Proposed HMM Module for Character Recognition

III. PRE-PROCESSING

Any image processing application suffers from noise like isolated pixels. This noise gives rise to ambiguous features which results in poor recognition rate or accuracy. Therefore a preprocessing mechanism has been executed before we could start with feature extraction methods. Here a sequence of operations is carried out in succession as shown in flow diagram .We have used median filter for its better performance to get rid of unwanted marks or isolated pixels. Thinning is performed to get the skeleton of character image so that the strokes could be conspicuous.

Fig. 4 Block Diagram for Pre-processing

IV. FEATURE EXTRACTION

Feature extraction is an important part of any type of pattern recognition. A better feature extraction method may yield better recognition rate by a given classifier. Therefore, much attention is paid to extract the suitable features from the pre-processed images. Our feature extraction process consists of Feature Extraction by Zoning Method

After pre-processing, the whole image is read in the form of matrix of size 150×150 and then is divided into 25 zones by means of non-overlapping window of size 30×30.Now features are extracted in two ways-

(a) First feature is extracted from each zone by finding total no. of white pixels of the zone and then dividing this number by the total no. of pixels of the zone.

$$F_n = \frac{1}{N}\sum_{i=0,j=0}^{10,10} I_{i,j} [\text{for } n^{th} \text{ zone}] \qquad (1)$$

(b) Second set of features is extracted in the form of vector distance. First the vector distance of each white pixel of a zone is calculated from the element at bottom left corner of the same zone. All such distances are summed up and finally the normalized vector distance is calculated by dividing the sum by the sum of all such distances for all pixels in the zone from the same reference.

$$D_{i,j} = \sqrt{i^2 + j^2} \qquad (2)$$

$$F_n = \frac{\sum_{I_{i,j}=1} D_{i,j}}{\sum_{I_{i,j}=0,1} D_{i,j}} \quad [I_{i,j} = \text{intensity at pixel position}(i, j)] \qquad (3)$$

To find the global feature, the same process is followed by taking the whole image as a single zone.

Therefore, our final observation sequence contains 156 observations obtained by global and local feature extraction
method , as shown below

$$O = [Z_G(6) \quad Z_L(150)] \qquad (4)$$

V. HIDDEN MARKOV MODEL

Hidden Markov Model (HMM) is a finite state machine in which a sequence of observations (O) is produced by this model but the corresponding sequence of states remains hidden within this model [9]. This HMM model can be defined as

$$\lambda = (\pi, A, B) \qquad (5)$$

where π is initial state probability vector, A is final state transition probability matrix and B is final observation probability matrix. The HMM model was initially used for speech recognition purpose, but later it has been proved that the HMM model can be efficiently utilized for other recognition process like character recognition, pattern recognition etc. In this paper , a closed left to right chain HMM model has been used for handwritten English characters recognition. A sketch of 5 states HMM model is shown in the figure below.

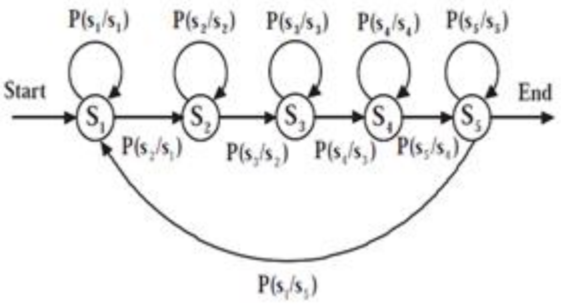


Fig. 7 Left to right chain HMM model with 5 states.

Baum-Welch algorithm has been used to train the HMM using observation sequence obtained from the feature vectors. At the end of training process, the obtained value of A and B are used for recognition purpose. Viterbi decoding algorithm has been used to decode the sequence of states of the HMM model λ for the sequence of observation O and it returns P (O/λ), the probability of generating the given sequence O by the HMM model λ.

VI. POST-PROCESSING

A post-processing block is included at the final stage of recognition process in order to provide special care to the highly confusing group of characters due to their high structural correlation factor (similarity). Few examples of such groups are mentioned below-

(1) O and Q,
(2) M and N,
(3) V and Y,
(4) C and O,
(5) B, K, R and P etc.

For each group , one or more new features have been extracted that can discriminate these characters with almost 100 percent accuracy. For example, O and Q can be easily differentiated using signature features [11], as shown in Fig.8-10.

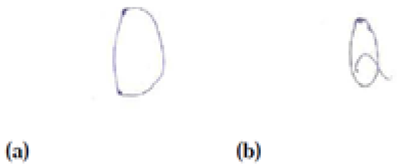


Fig. 8. Samples of Character Image for Post-processing (a) Character O and (b) Character Q

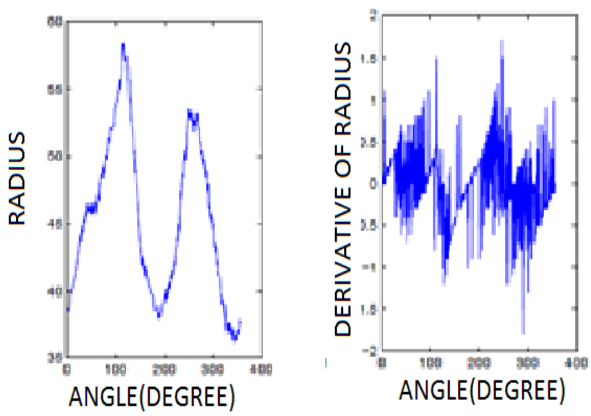


Fig. 9 Signature and derivative of signature plot for character O shown in fig.8 (a).

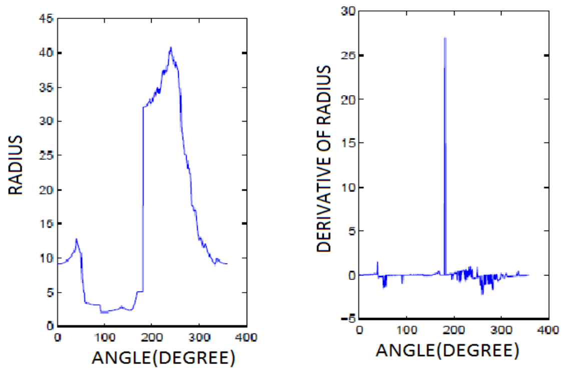


Fig. 10 Signature and derivative of signature plot for character Q shown in fig.8 (b).

These show that the differentiation of signature plot of Q contains very large spike that can be utilised to distinguish this (Q) from the character O using a threshold criteria. It should be noted that, this signature feature is not used to train the HMM models of all characters. The effect of this post-processing block is presented in the next section providing some experimental studies.

VII. EXPERIMENTS AND RESULTS

A total of 13000 samples are collected from 100 persons. Each writer wrote 5 set of A-Z characters. Each character image is converted to a fixed size of 150×150 pixels . Feature extraction method has been applied on these samples and then these feature values are quantized and encoded to the eleven symbols in order to create sequences of observation symbols. First 100 samples of each character are used to train the corresponding character HMM. Rest 400 samples are used to test our HMM classifier. For our experiment we have started with only 5 state model but it is observed that as the no. of states of HMM model is increased, the corresponding recognition rate is also improved. Finally, the expected results were obtained with 36 states HMM model as shown in tables. Table I, shows the effectiveness of our proposed model of taking multiple HMM for a single character A.

TABLE 1
IMPROVEMENT of RECOGNITION RATE for CHARACTER 'A' USING MULTIPLE HMM

Chara-cter	Single HMM Model Recognition Rate (%)	Multiple HMM Model Recognition Rate (%)
A	81.25	91.5
W	82.5	91.25

In Table II, we have shown final recognition rate of our character recognition system using post-processing and it is compared with result obtained without post processing technique. This produces an average recognition rate of 92.67%.

TABLE II
RECOGNITION RATE WITH or WITHOUT POST-PROCESSING USING
PROPOSED MULTIPLE HMM MODEL

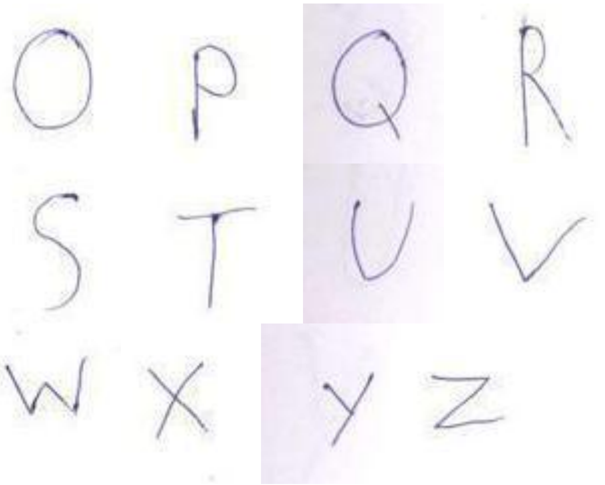
Char-acter	Recognition Rate(%)		Char-acter	Recognition Rate(%)	
	Without pp	With pp		Without pp	With pp
A	91.5	91.5	N	93.25	94.5
B	88.25	90.12	O	95.50	96.55
C	92.75	94.25	P	90.25	92.25
D	83.08	83.08	Q	88.25	89.16
E	89.24	89.24	R	86.75	89.25
F	92.36	92.36	S	96.50	96.50
G	88.12	88.12	T	97.23	97.23
H	98.75	98.75	U	83.50	83.50
I	96.25	96.25	V	91.81	94.75
J	82.50	82.50	W	97.25	97.25
K	85.50	87.75	X	99.35	99.35
L	95.9	95.9	Y	94.78	97.15
M	97.25	99.73	Z	92.50	92.50

VIII. CONCLUSION

In this paper, an approach has been made to increase the rate of recognition of handwritten character by finding both local and global features. Multiple level HMM model is designed for some specific letters having wide range of variations from writer to writer. In the last section, a trial has been made to put a line of demarcation between similar looking characters.
All these specialties of this paper have made us obtain an average accuracy of 92.67%. For a few number of letters, the accuracy rate is even close to 100%.

IX. DATA-SET

One set of collected data has been shown for reference



ACKNOWLEDGMENT

Thanks to the authority of Bengal College of Engineering and Technology, Durgapur (W.B.) to provide with WI-FI connection and other facilities like scanning etc. to carry out our research works.

REFERENCES

[1] U. Bhattacharya, and B. B. Chaudhury, "Handwritten numeral databases of Indian scripts and multistage recognition of mixed numerals", IEEE Trans. Pattern analysis and machine intelligence, vol. 31, No. 3, pp. 444-457, 2009.
[2] U. Pal, T. Wakabayashi and F. Kimura, "Handwritten numeral recognition of six popular scripts", Ninth International Conference on Document Analysis and Recognition, ICDAR07, Vol.2, pp.749-753, 2007.
[3] V. K. Govindan and A. P. Shivaprasad,"Character Recognition A review", Pattern recognition, vol.23, no.7, pp.671-683, 1990
[4] J. Pradeep, E. Srinivasan and S. Himavathi, "Diagonal Based Feature Extraction for Handwritten Alphabets Recognition System Using Neural Network", International Journal of Computer Science and Information Technology (IJCSIT),, vol. 3, no. 1, pp. 27-38, Feb 2011
[5] G. Kim, V. Govindaraju, and S. Srihari, "Architecture for handwritten text recognition systems",International Journal on document Analysis and Recognition (IJDAR), vol. 2, pp. 37-44, 1999.
[6] U. V. Murti, and H. Bunke, " Using a statistical language model to improve the performance of an HMM-basis cursive handwriting recognition system", International Journal of Pattern Recognition and Artificial Intelligence, 2001;15:65-90.
[7] S. Gunter, and H. Bunke, "Off-line cursive handwriting recognition using multiple classifier systemson the influence of vocabulary, ensemble, and training set size", Optics and Lasers in Engineering, vol. 43, pp. 437-454,2005.
[8] M.Hanmandlu,A.V.Nath,A.C.Mishra and V.K.Madasu "Fuzzy Model Based Recognition of Handwritten Hindi Numeral using Bacterial Forging" 6th IEEE/ACIS International Conference on Computer and Information Science(ICIS 2007) 0-7695-2841-4/07(C)2007 IEEE(IEEE Computer Society)
9. L. R. Rabiner ,"A Tutorial on Hidden Markov Model and selected applications in speech recognition ,"Proceedings of the IEEE,Vol.77,no.2,pp.257-286,1989