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ZONE THEORY APPLIED TO BOOST RECOGNITION RATE OF HMM BASED SYSTEM

Binod Kumar Prasad

Department of Electronics and Communication Engineering,
Bengal College of Engineering and Technology, Durgapur, INDIA

E-mail: binod.krpr@rediffmail.com

Goutam Sanyal

Department of Computer Science and Engineering,
National Institute of Technology, Durgapur, INDIA

E-mail: nitgsanyal@gmail.com

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. Study reveals that a promising recognition system should have two essential factors viz. a good combination of features and a strong classifier. So far the matter of combination of features is there; in this paper features based on the concept of Zone theory have been applied in unison with Gradient, Projection and curvature features to represent a character image efficiently. The success of automatic speech recognition systems based on HMM has motivated recent attempts to apply similar methods to character recognition. It has been found that the limited recognition rate of 1D HMM Character Recognition System and requirement of respectively larger no. of samples for construction of 2D HMM system, HMM based character recognition system is lagging behind other systems so far assured practical application is concerned. The purpose of this research work is to enhance the recognition rate of an off-line handwritten Character Recognition System using 1D HMM with an ideal combination of features followed by decreased algorithm complexity, so that the processing time could be reduced (very close to real time system) while providing higher recognition accuracy. Ultimately, it could be implemented practically with full confidence. The overall efficiency of the system has been found to be 98.46%

Keywords:

Hidden Markov Model; Sobel masks; gradient feature; curvature features and projected histogram.

I. Introduction

The off-line handwriting recognition (OHR) still remains an active area for research towards exploring the newer techniques that would help improving recognition accuracy. It is because of the fact that several applications including mail sorting, bank processing, document reading and postal address recognition require offline handwriting recognition systems. Most of the systems reported in literature until today consider constrained recognition problems based on vocabularies from specific domain e.g., the recognition of handwritten check amounts [1] or postal address [2]. Free handwritten recognition, without domain specific constraints and large vocabularies was addressed only recently in a few papers [3], [4]. The recognition rate of such system is still low and there is a need of improvement [5].

In previous paper [6], Global gradient feature, Local gradient feature, projection feature and curvature feature were considered for identification of character image. But for some characters like G, M, S, Y; the recognition accuracy was found to be lower than the rest ones. Study discloses that Zonal concept reproduces better recognition rate. So, in this paper Local gradient feature has been replaced with features based on Zoning theory in order to minimize the algorithm complexity.

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 [7]. These specialties of zoning method have provoked interest to apply it in unison with already used efficient features in earlier publication.

In [7] 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 here the sum of individual distances of bright pixels has been normalized by the summed up distance of all the pixels in the respective zone.

The method has been applied to a particular image in two ways-(1) by keeping the image in original form (2) by shearing the image horizontally in both positive and negative directions. Again, features have been extracted both globally and locally as explained in the section titled Feature Extraction.

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. Multiple HMM models are used for these characters whereas for other characters, single HMM model has been resorted to 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. $P(O/\lambda)$, 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.

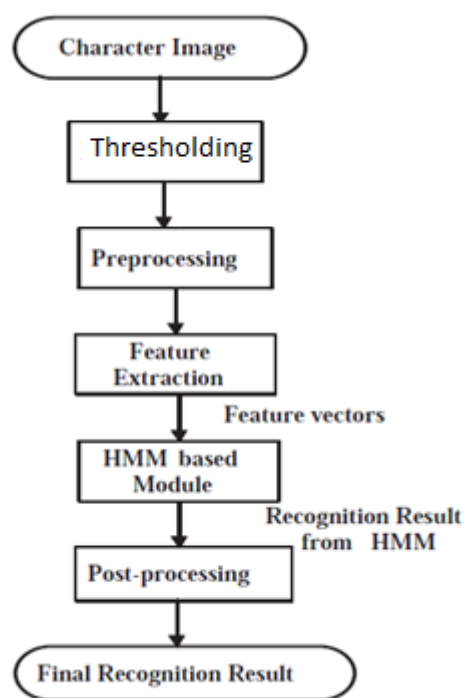


Fig. 1 System Overview

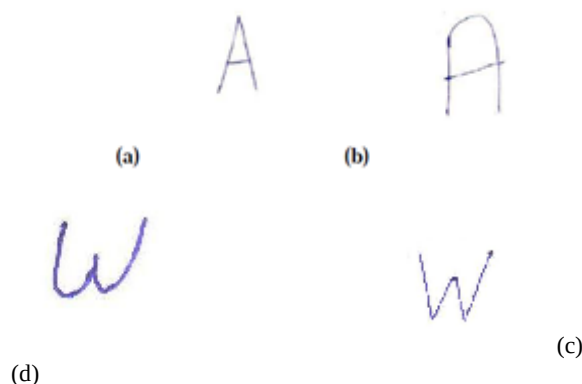


Fig.2. Two completely different formats for handwritten character A (a) A1 (b) A2 and for character W (c) W1 (d) W2

III. Thresholding

The collected samples are converted into a standard dimension of 150×150 pixels before executing the steps of pre-processing. It might happen that training or testing samples are of dimension beyond 150×150 pixels. In such cases, the recognition system will not respond. So, to discard such samples, dimensionwise thresholding has been done.

IV. 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 strokes could be conspicuous.

V. Feature Extraction Methods

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 preprocessed images. Our feature extraction process consists of -

A. 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.

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

(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.

$$D_{ij} = \sqrt{i^2 + j^2} \quad (2)$$

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

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 52 observations obtained by global and local feature extraction method, as shown below

$$O = [Z_G(2) Z_L(50)] \quad (4)$$

B. Gradient Features

To compute the density of line segments in the quantized direction we use only two masks - Horizontal sobel mask and Vertical sobel mask. Magnitude and phase of the gradient obtained by Sobel masks are calculated as below

$$\text{Magnitude: } M(x, y) = \sqrt{[S_H^2(x, y) + S_V^2(x, y)]} \quad (5)$$

$$\text{Phase: } \phi(x, y) = \tan^{-1} \frac{S_H(x, y)}{S_V(x, y)} \quad (6)$$

Phase is quantized in eight directions as shown in Fig. 6. For each quantized phase value, corresponding magnitudes are added to get the total strength in that direction. To get the feature within finite number of symbols (here eleven symbols are used), magnitudes are normalized and quantized. Finally, we consider four global gradient (G) features combining following pairs- $(0^\circ, \pm 180^\circ)$, $(45^\circ, -135^\circ)$, $(90^\circ, -90^\circ)$ and $(135^\circ, -45^\circ)$.

C. Projection Features

After preprocessing the two dimensional binary handwritten character image $f(x, y)$ is projected to X and Y axis respectively and we get following two histograms.

Projection on X-axis:

$$U(i) = \sum_{k=1}^N f(i, k), \quad 1 \leq i \leq N \quad (7)$$

Projection on Y-axis:

$$V(j) = \sum_{k=1}^N f(k, j), \quad 1 \leq j \leq N \quad (8)$$

From each histogram we find three features, namely, mean, variance and entropy as given below

$$\mu_x = \frac{1}{N} \sum_{i=1}^N X(i) \quad (9)$$

$$\sigma_x^2 = \frac{1}{N} \sum_{i=1}^N (X(i) - \mu_x)^2 \quad (10)$$

and

$$E_x = - \sum_{i=1}^N e_{xi} \log(e_{xi}) \quad (11)$$

$$\text{Where } e_{xi} = \frac{X(i)}{\sum_{i=1}^N X(i)} ; \quad X = U \text{ and } V \quad (12)$$

Therefore, from projection method we find total six features as below

$$P = [\mu_U \quad \sigma_U^2 \quad E_U \quad \mu_V \quad \sigma_V^2 \quad E_V]$$

D. Curvature Features

We have taken four curvatures measured from top (C_T), bottom (C_B), right side (C_R) and left side (C_L) of the character image. Thus the curvature feature (C) consists of four observations as below

$$C = [C_T \quad C_B \quad C_R \quad C_L]$$

VI. 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[8]. This HMM model can be defined as

$$\lambda = (\pi, A, B) \quad (13)$$

where π is initial state probability vector, A is final state transition probability matrix and B is final observation probability matrix. In this paper a closed left to right chain HMM model has been used for handwritten English characters recognition.

Baum-Welch algorithm has been used to train the HMM using observation sequence (O) obtained from the feature vectors. At the end of training process, the final values of A and B are obtained which are used for recognition purpose.

Viterbi decoding algorithm is applied to decode the sequence of states of the HMM model λ for the sequence of observation O and it returns $P(O/\lambda)$, the probability of generating the given sequence O by the HMM model λ .

VII. Post-processing

A post-processing block is included at the final stage of recognition process in order to provide special care to the highly confused 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 are to be extracted that can discriminate these characters with almost 100 percent accuracy. For example, O and Q has been differentiated using signature features [9]

For example, O and Q can be easily differentiated using signature features as shown in Fig.3-5.

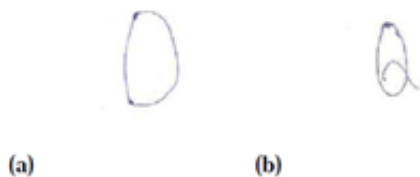


Fig.3. Samples of Character Image for Post-processing (a) Character O and (b) Character Q

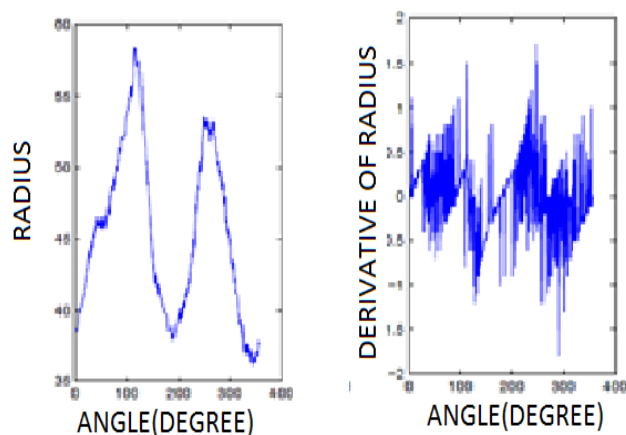


Fig. 4. Signature and Derivative of Signature Plot for Character O Shown in Fig.8 (a).

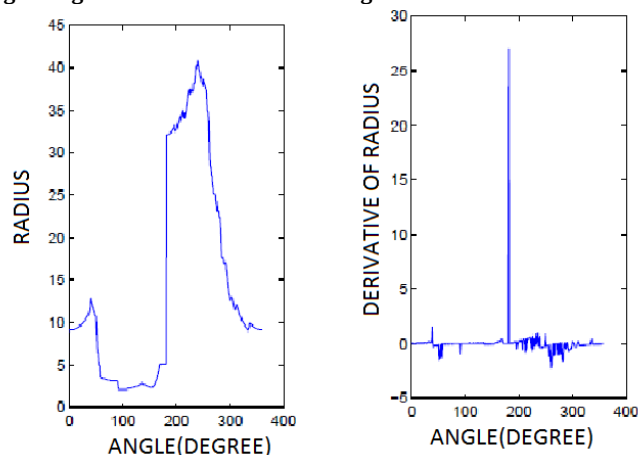


Fig. 5. Signature and Derivative of Signature Plot for Character Q Shown in Fig.8(b).

These show that the differentiation of signature plot of Q contains very large spike that can be utilised to distinguish Q from the character O using a threshold criteria.

VIII. Experiment and Results

A total of 13000 samples are collected from 100 persons. Each writer wrote 5 sets of A-Z characters. Each character image is converted to a fixed size of 150×150 pixels. We have applied our feature extraction method 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. The experiment has been 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 result is obtained with 36 states HMM model as shown in tables. Table 1, shows the effectiveness of our proposed model of taking multiple HMM for the characters A and W.

Table 1 Improvement of recognition rate for character A&W using proposed model

Character	Single HMM Model Recognition Rate (%)	Multiple HMM Model Recognition Rate (%)
A	85.25	98.5
W	89.5	98.0

In Table 2, 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 98.46%.

Table 2 Recognition rate with and 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	98.55	98.55	N	98.85	99.20
B	97.54	98.45	O	96.50	99.50
C	98.00	99.50	P	96.75	98.25
D	98.00	98.00	Q	96.50	99.00
E	97.25	97.25	R	93.75	98.25
F	98.20	98.20	S	98.25	98.25
G	95.50	97.25	T	97.75	97.75
H	98.00	98.00	U	97.50	97.50
I	99.50	99.50	V	97.15	97.90
J	98.00	98.00	W	98.00	98.50
K	97.25	98.70	X	98.50	98.50
L	98.80	98.80	Y	94.55	98.90
M	97.50	99.75	Z	98.80	98.80

IX. 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. The purpose of the paper is to improve the recognition accuracy of some specific letters G, M, S and Y which was not achieved in paper [1]. The purpose is served, as is clear from Table 2 but at the same time, recognition rate of some letters has fallen down a bit.

However the average accuracy is 98.46% comparatively better than that achieved in paper [1] i.e., 98.26%.

X. Data-Set

One set of collected data has been shown for reference



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