Kannada Handwritten Numeral Recognition System using Fuzzy Reasoning Technique

Ashoka H N
Department of Electronics and Communication Engg.,SMIT, Sikkim, INDIA

Manjaiah D H
Department of Computer science, Mangalore University Mangalore, INDIA

Rabindranath Bera
Department of Electronics and Communication Engg.,SMIT, Sikkim, INDIA

ABSTRACT

This paper presents Kannada handwritten numeral recognition system using fuzzy reasoning technique. The Kannada handwritten numeral database required for the experimentation is collected from the different individuals and preprocessed to obtain the binary images for feature extraction. The binary images are partitioned into a number of regions and extracted one feature from each by the zoning technique for their representation. The knowledge base is build using the statistical information involved in interclass region features. The features of unknown samples matched with the knowledge base and made the fuzzy reasoning for their classification. On experimentation with the training and testing samples, found better classification and recognition rate.

General Terms

Zoning Feature extraction, Kannada handwritten numeral recognition

Keywords

Fuzzy reasoning, Kannada numeral database, knowledge base

1. INTRODUCTION

Karnataka is the state of south India and Kannada is the official state language. It has separate numeral symbols and used extensively to write PIN code, bank cheques, vehicle and street numbers in the state. Handwritten Kannada numeral recognition is a complex task due to the intra and interpersonal variations in writing style like size, shape, etc. In 40-50 years of work in the optical character recognition (OCR), human still outperform the most powerful off-line character recognition system developed so for due to extensive variations handwriting styles[1]. Researchers proposed different numeral recognition systems based on the preprocessing, feature extraction, selection and classification techniques.

The feature extraction is an important step in the pattern recognition system. It extracts a set of information associated in the pattern or from its sub regions for their representation [2-5]. The set of features (features vector) extracted represents the input pattern in minimum dimension and it reduces the complexity of classification and recognition system. The features class discriminating ability decides their quality. The quality feature will have the maximum inter-class variation and minimum intra-class variation. The commonly used feature extraction methods for pattern recognition system are statistical, global transformation and series expansion, geometrical and topological techniques [2, 6, 7].

U. Pal et al [8] extracted 100 features for Kannada numeral recognition by the extensively used zoning technique of statistical method for handwritten character and numeral recognition. Rajashekararadhya and Vanaja [9] extracted two features from the 50 zones and in total 100 features for the south Indian scripts Kannada, Telugu, Tamil, and Malayalam handwritten numerals representation. They reported a recognition rate of 95% - 99% by the nearest neighbor classifier and feed forward back propagation neural network classifiers. Dinesh Acharya et.al [10] extracted 44 potential different types of structural features for the recognition of isolated handwritten Kannada numerals and reported a recognition accuracy of 98 % from the fuzzy k-NN classifiers. Dhanrda et.al [11] divided the binary image of a digit into 64 zones and computed feature for each zone by the pixel density for bilingual Kannada and Telugu digits recognition. They reported a recognition rate of 95.5% and 99.83% with K-NN classifier for Kannada and Telugu numerals respectively.

From the above it is clear that, for Indian scripts handwritten numeral digits representation, authors extracted more number of features by the zoning technique. When the more number of features used to represent the pattern, intern it will increase the complexity of classifier. In view of this, an attempt is made to represent the input pattern with less number of features by the zoning technique. The knowledgebase (KB) is build for Kannada handwritten numerals and used fuzzy reasoning technique for unknown sample recognition.

2. METHODOLOGY

The proposed Kannada handwritten numeral recognition system using fuzzy reasoning technique is given in Figure 1. The numeral images collected from the different individuals are scanned and preprocessed to obtain the binary images for feature extraction. The binary images are fitted in a particular window size and extracted feature vectors for their representation. The feature vectors are divided into training and testing data features. The training samples feature vectors are used to construct the knowledge base. The feature vectors of testing samples matched with the knowledge base and made fuzzy reasoning for their class label.

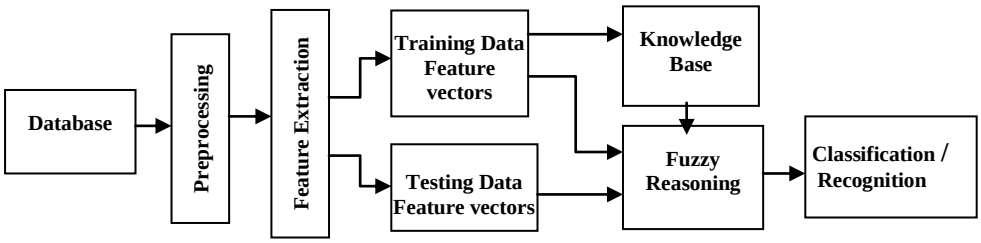

Fig 1: The methodology for Kannada numeral recognition system using fuzzy reasoning technique.

3. DATABASE AND FEATURE EXTRACTION

The Kannada numeral database required for the experimentation is collected from the 125 different individuals. Each writer was requested to write two sets of 0-9 Kannada numerals and a set for training data and another for testing data. In total, the database used has 2500 numerals. The data collected on A4 sheets are scanned using HP-scan jet 5400c at 300dpi and stored in the separate files after segmentation. The MATLAB built-in functions are used to obtain the resized binary images in a window of size 12x12 for isolated handwritten numerals. The binary images stored in 12x 12 are partitioned into 3x3 sixteen square regions for feature extraction. The presence 1s in each region is transformed to a real number. This value is proportional to the number of 1s in the region and called feature value. For each region, this value is computed by the two approaches A1 and A2 [12] and used separately to build the KB. In the A1 approach, irrespective of their position, the density 1s pixels in a region are transformed as real number. In A2 approach, used the position of 1s pixel in a region to compute a real number by measuring their co-ordinate distance [13].

4. KNOWLEDGE BASE AND FUZZY REASONING TECHNIQUE

In order to classify the unknown samples constructed the KB of each feature for all the numeral classes and fuzzy reasoning technique [14] for recognition. In brief, the KB construction and fuzzy reasoning technique is discussed in this section. The mean feature vector, $\bar{f}$ and the standard deviation, σ is computed for each numeral class by their training sample feature vectors. Fig.2 shows the KB triangle of a region constructed for kth class rth region. Each numeral class has KB triangle equal to the number of features extracted.

The base of KB triangle of kth class rth region is fixed from the minimum ($f_{r\min}^{k}$) and maximum ($f_{r\max}^{k}$) feature values of a region. These values are computed using the mean ($\bar{f}_r^{k}$) and the standard deviation (σ_r^{k}) of kth class rth region using the Eq. (1) and Eq. (2). To keep the value of membership values between 0-1, chosen the height of a triangle to a maximum possible value '1' at the center of base of a KB triangle.

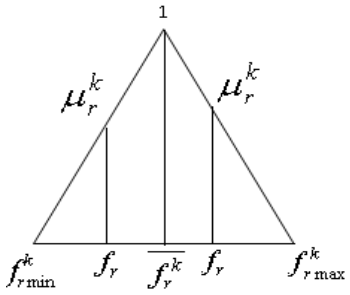

Fig.2. the KB of kth class rth region triangle

$$f_{r\min}^{k} = \bar{f}_r^{k} - \alpha\sigma_r^{k} \quad (1)$$

$$f_{r\max}^{k} = \bar{f}_r^{k} + \alpha\sigma_r^{k} \quad (2)$$

The base of a KB triangle is widened by multiplying the standard deviation (σ_r^{k}) with a deviator 'α' to handle the variability involved in the patterns. This increases the performance of the classifier. The value of 'α' is found experimentally by varying its value from 0.1 to 3.0.

The unknown sample feature vectors are matched with all the KB triangles of each numeral class to measure the similarity. If the feature value (f_r) of region 'r' matches with the KB, then the similarity is measured and assigned the membership value. The membership value is found from the height at the feature value in the KB triangle. This is repeated for all the regions of unknown sample and then computed the algebraic sum of the membership values for all the numeral classes. The class having maximum algebraic sum is assigned to the unknown sample.

5. RESULTS AND DISCUSSION

The experimental results of Kannada handwritten numeral database is presented in this section. The database is divided into a training data and testing data and their feature vectors are extracted for each sample by the two feature extraction approaches A1 and A2. To construct the KB, the mean feature vectors for ten numeral classes are computed from the training sample feature vectors. The mean feature vectors of individual classes by the approaches A1 and A2 is given in Fig.3 (a) and Fig.3 (b) respectively. From the graph, it is observed that the mean feature values of individual numeral classes are different for most of the regions. These indicate that they are distinctive to represent their classes.

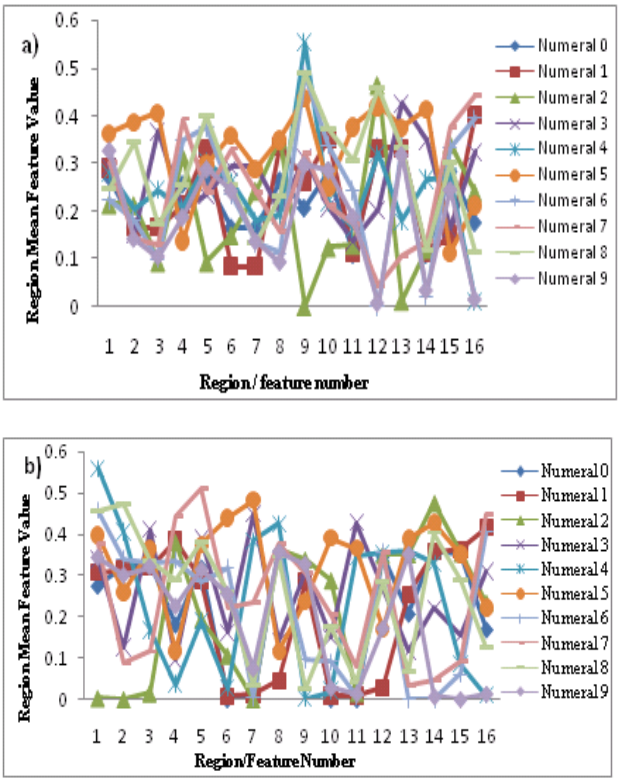

Fig.3. The mean feature vectors of Kannada handwritten numerals. a) Features extraction method A1, b) Features extraction method A2.

Since the numeral samples are collected from the different individuals, their feature vectors vary due to the writing styles. The variation involved from their mean region features is measured by the standard deviation for all the individual class. If the standard deviation is small, it indicates that the minimum variation in the samples. The standard deviation computed by the two feature extraction approaches A1 and A2 for the individual numeral classes is given in the Fig. 4(a) and Fig. 4(b) respectively.

The standard deviation computed for each region of the individual numeral class is used to construct their KB. The feature vector of unknown sample is matched with the KB of all the regions to find their class label. An example, 125 samples of numeral class '2' is shown to the classifier constructed by the features extracted by the method approach A1 with different value of α. The results are tabulated in the Table 1. From the table 1, it is seen that for lower value of α (α=0.1 to 0.4) few samples are recognized correctly as '2'. When the value of α is most of the samples recognized correctly. Repeated this procedure for other numeral classes and found the recognition rates by the two classifiers build using the features of approaches A1 and A2. The results obtained by the A1 and A2 with the different value of α are given in the Fig.5 and Fig.6 respectively.

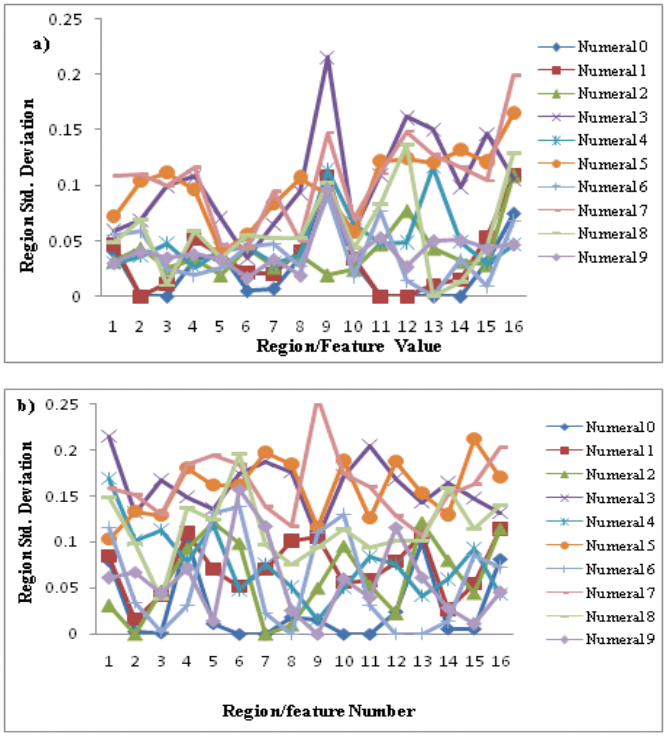

Fig.4. Standard deviation of regions computed for individual numeral classes. a) Feature extraction method A1, b) Feature extraction method A2.

Table.1. the recognition result of 125 testing samples of numeral class '2 ' with different value of α by the method A1

α	Numeral classes									
	0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
0.1	0	0	70	3	8	5	20	17	2	0
0.2	0	0	79	0	5	3	13	25	0	0
0.3	1	0	77	0	1	2	16	26	2	0
0.4	2	0	79	0	1	2	13	26	2	0
0.5	2	0	98	0	0	0	6	17	2	0
0.6	1	0	114	0	0	0	0	8	2	0
0.7	0	0	118	0	0	0	0	5	2	0
0.8	0	0	121	0	0	0	1	2	1	0
0.9	0	0	121	0	0	0	0	3	1	0
1.0	0	0	123	0	0	0	0	2	0	0
1.1	0	0	123	0	0	0	0	2	0	0
1.2	0	0	123	0	0	0	0	2	0	0
1.3	0	0	123	0	0	0	0	2	0	0
1.4	0	0	123	0	0	0	0	2	0	0
1.5	0	0	123	0	0	0	0	2	0	0
1.6	0	0	123	0	0	0	0	2	0	0
1.7	0	0	123	0	0	0	0	2	0	0
1.8	0	0	123	0	0	0	0	2	0	0
1.9	0	0	124	0	0	0	0	1	0	0
2.0	0	0	124	0	0	0	0	1	0	0
2.1	0	0	124	0	0	0	0	1	0	0
2.2	0	0	124	0	0	0	0	1	0	0
2.3	0	0	124	0	0	0	0	1	0	0
2.4	0	0	124	0	0	0	0	1	0	0
2.5	0	0	124	0	0	0	0	1	0	0
2.6	0	0	124	0	0	0	0	1	0	0
2.7	0	0	124	0	0	0	0	1	0	0
2.8	0	0	124	0	0	0	0	1	0	0
2.9	0	0	124	0	0	0	0	1	0	0
3.0	0	0	125	0	0	0	0	0	0	0

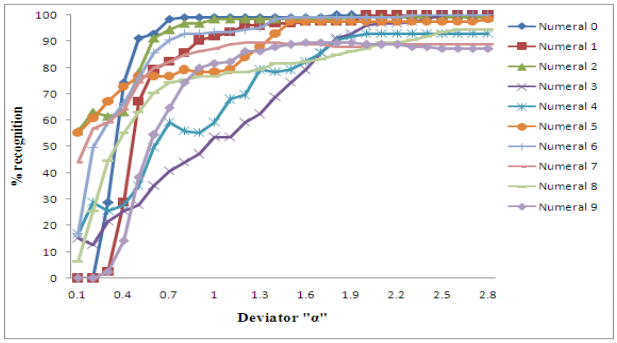

Fig. 5. The performance of recognition system developed from the features extracted by the approach A1.

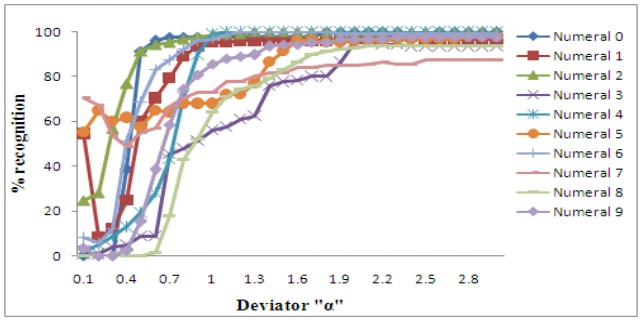

Fig. 6. The performance of recognition system developed from the features extracted by the approach A2.

From the Fig.5 and Fig. 6, it is observed that the percentage recognition rate is high for numeral class 0 and 2 at α=0.6 onwards. However, the recognition rate for other numeral classes is improved gradually with the increased value of α. The overall recognition rate for all the numeral classes is maximum when the value of α is more than 2.0 in both the methods. Therefore, assigned this value to α and used for the recognition. At the value of α =2.0, the recognition rate is low for numeral class 7 in both the methods A1 and A2 and is around 86%. The recognition rate is low in the method A1 for numeral 9. This is because Kannada handwritten numerals 7 and 9 have the similarity with 2 and 6 of numerals. However, the overall recognition rate of 96% and 96.4% is obtained by the methods A1 and A2 respectively.

6. CONCLUSIONS

Following conclusions are drawn from the experimental results. From the mean feature vectors, it is clear that they are class distinctive. The feature value of regions depends on the total number of one's present in both the feature extraction methods. The KB constructed from the variation involved in the training samples can be used to classify the unknown samples. The fuzzy reasoning technique is simple and it classifies the unknown Kannada numeral samples by the KB constructed from the less number of training samples. The fuzzy reasoning technique results better recognition rate and is suitable for Kannada handwritten numeral recognition.

7. REFERENCE

[1] Hiromichi Fujisawa, "Forty years of research in character and document recognition - an industrial perspective" Pattern Recognition, Vol.41, 2008, pp.2435 – 2446,

[2] Anil K. Jain, Robert P.W. Duin, and Jianchang Mao, "Statistical Pattern Recognition: A Review" IEEE Transactions on Pattern Analysis And Machine Intelligence, Vol. 22, No. 1, 2000, pp. 4-38.

[3] Husni A. Al-Muhtaseb , Sabri A. Mahmoud and, Rami S. Qahwaji "Recognition of off-line printed Arabic text using Hidden Markov Models", Signal Processing Vol.88,No. 12, 2008 pp. 2902–2912.

[4] Sabri A. Mahmoud "Recognition of writer-independent off-line handwritten Arabic (Indian) numerals using hidden Markov models." Signal Processing, Vol.88, No. 4, 2008, pp - 844-857.

[5] G.Y. Chen, W.F. Xie, Pattern recognition with SVM and dual-tree complex wavelets, Image and Vision Computing Vol. 25, 2007, pp 960–966.

[6] Oivind Due Trier, Anil k. Jain and Torfinn Taxt, "Feature Extraction Methods for Character Recognition--A Survey" Pattern Recognition, Vol. 29, No. 4, pp. 641-662, 1996.

[7] Nafiz Arica, Fatos T. Yarman-Vural, "An Overview of Character Recognition Focused on Off-line Handwriting", IEEE Transactions on system Man. Cybernetics-Part C: Applications and Reviews, vol. 31 no. 2, pp.216-233, May 2001.

[8] Umapada Pala, Partha Pratim Royb, Nilamadhaba Tripathya and Josep Lladósb, "Multi-oriented Bangla and Devnagari text recognition", Pattern Recognition, Vol. 43, No.12, 2010, pp 4124-4136.

[9] Rajashekararadhya S.V. and Vanaja Ranjan P., "Handwritten numeral recognition of Kannada script", Proceedings of the international workshop on Machine Intelligence Research (MIR day,GHRCE- Nagpur) 2009, pp-80-86.

[10] Dinesh Acharya U, N V Subba Reddy and Krishnamoorthi, "Multilevel classifiers in recognition of Handwritten Kannada numerals", World Academy of Science, Engineering and Technology vol.18, 2008, pp-278-283.

[11] Dhandra B.V., Gururaj Mukarmbi, and Mallikarjun Hangarge, "A script independent approach for handwritten bi-lingual Kannada and Telugu digits recognition" International Journal of Machine Intelligence, Vol.3 No. 3, 2011, PP- 155 -159.

[12] Ashoka, H. N., D. H. Manjaiah, and Rabindranath Bera. "Feature Extraction/Selection and Statistical Classification Technique for Character Recognition." International Journal of Advanced Research in Computer Science and Software Engineering" Vol.2 no.5,2012, pp. 414-420.

[13] Hanmandlu M., and Murthy O.V.R., "Fuzzy model based recognition of handwritten numerals" Pattern Recognition, vol. 40, 2007, pp 1840 – 1854.

[14] Ashoka H.N, Manjaiah D.H and Rabindranath Bera. "A Fuzzy Reasoning Technique for Pattern Recognition". International Journal of Computer Applications 49(12), July 2012 pp19-23.